

Part I: Joint cosmological constraints from the SPTxDES 6x2pt analysis

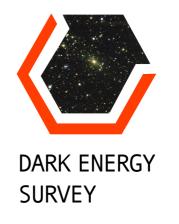
Based on:

https://arxiv.org/abs/2203.12439 (Methodology paper)

https://arxiv.org/abs/2203.12440 (Measurements paper)

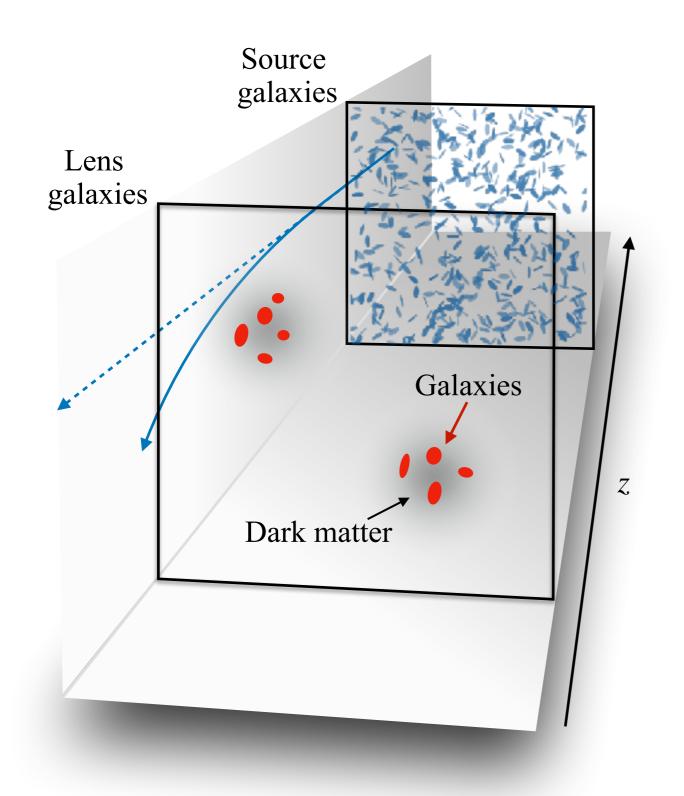
https://arxiv.org/abs/2206.10824 (Cosmology paper)

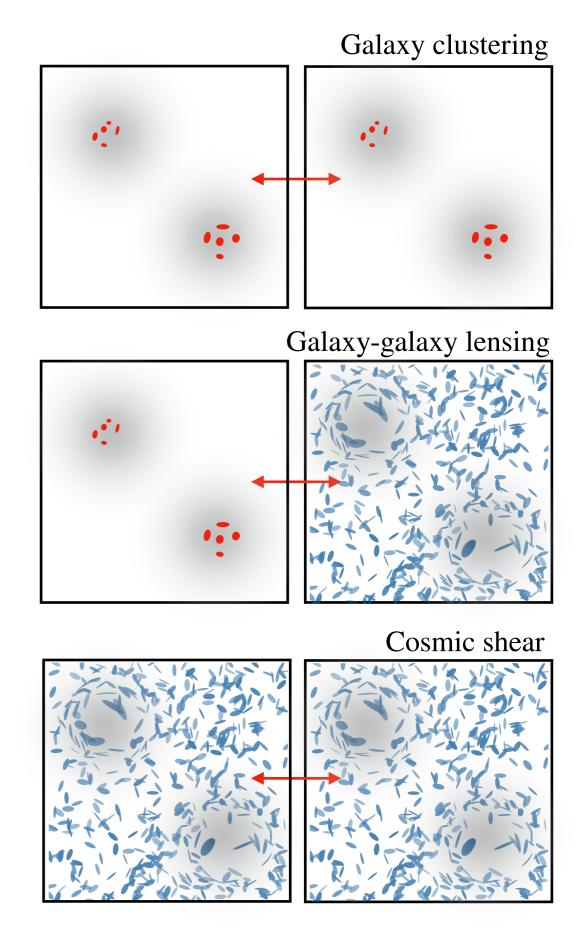
Work in collaboration with Eric Baxter (UHawaii), Chihway Chang (UChicago//KICP) and many others from SPT and DES collaborations





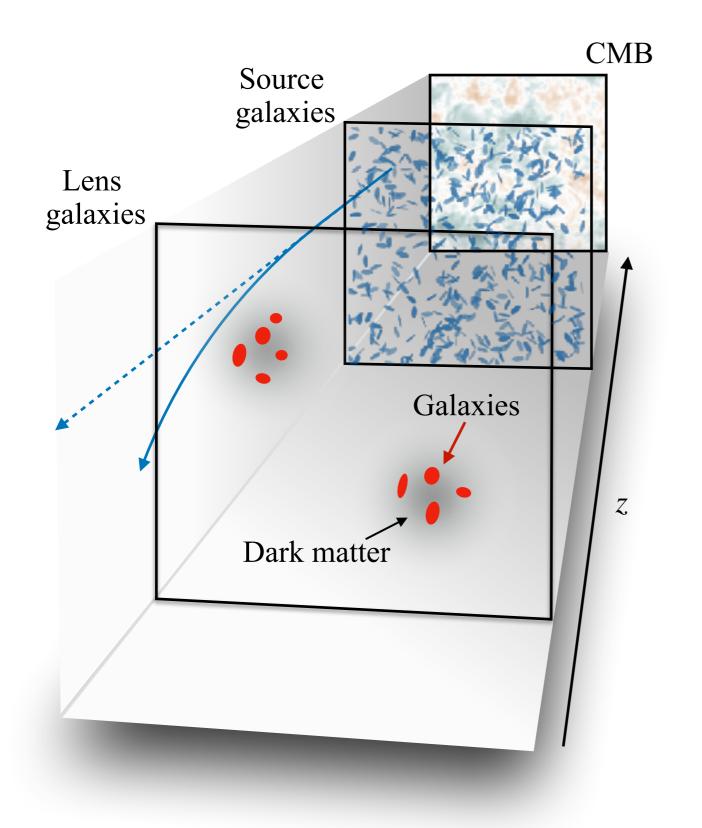
Overview

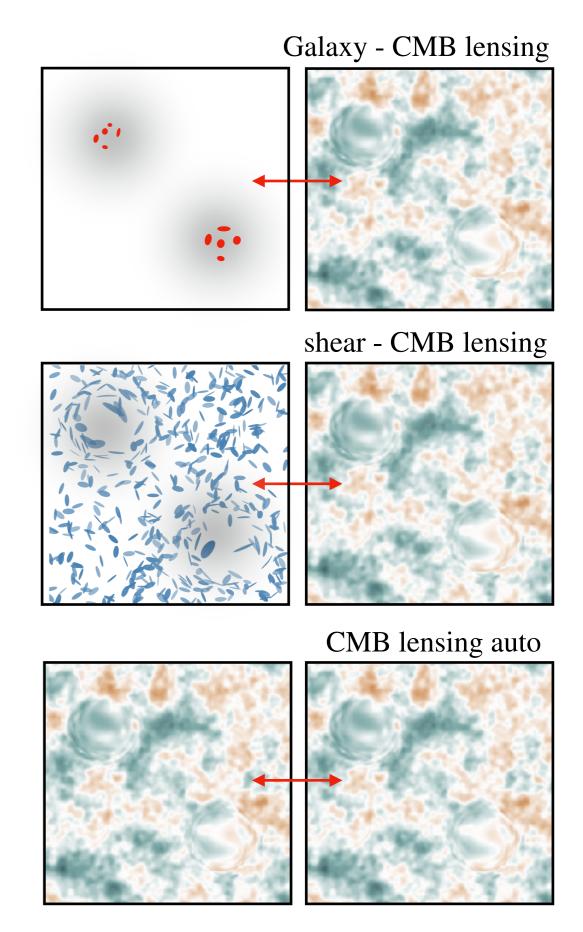




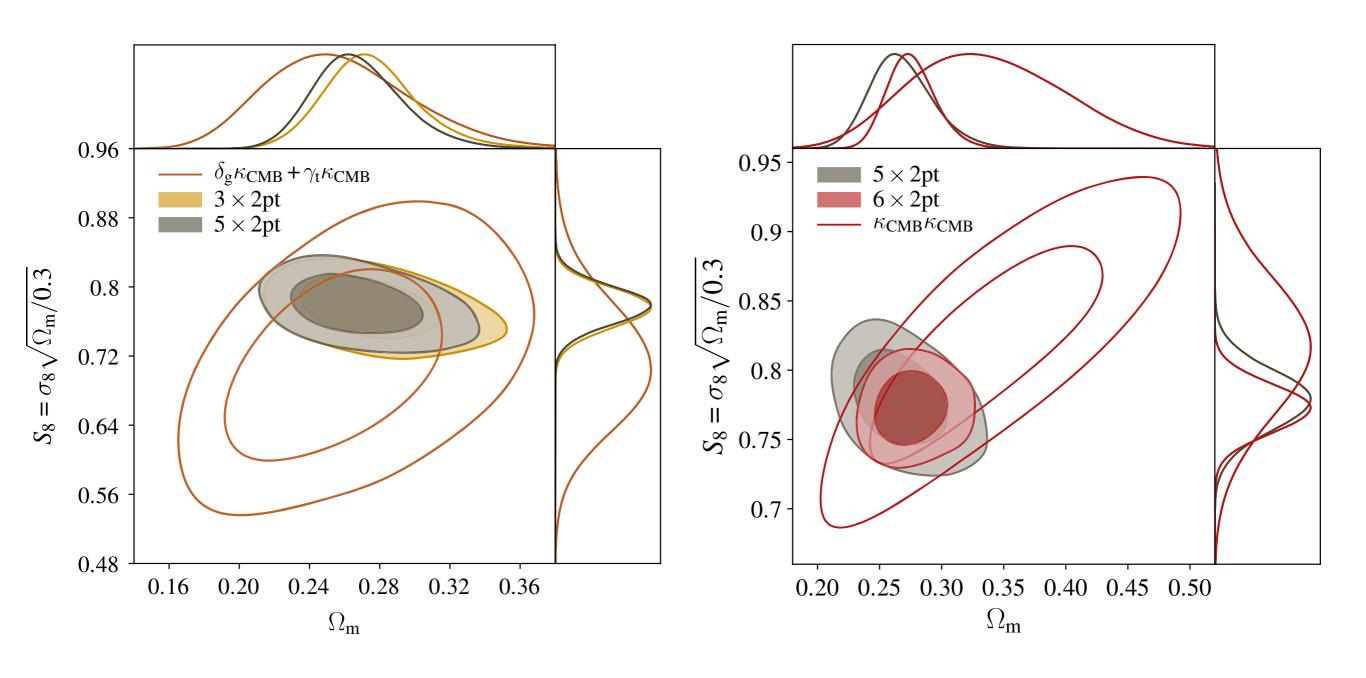
Three 2pt functions = "3x2pt"

Overview

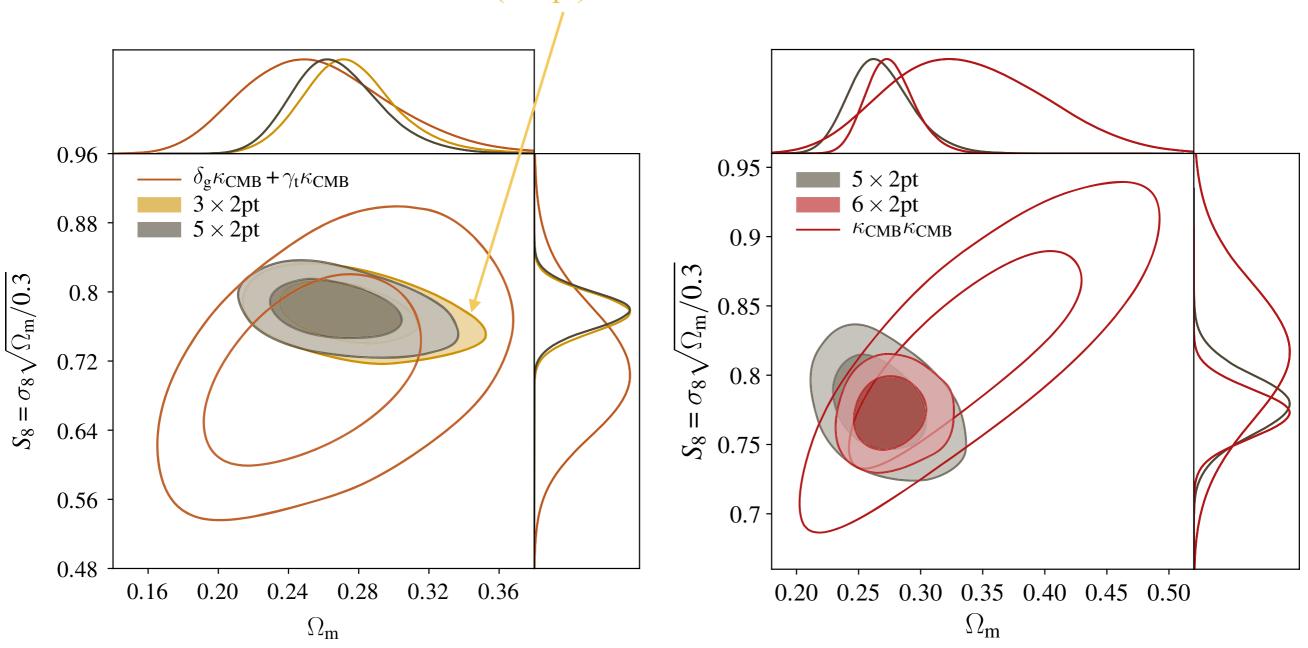




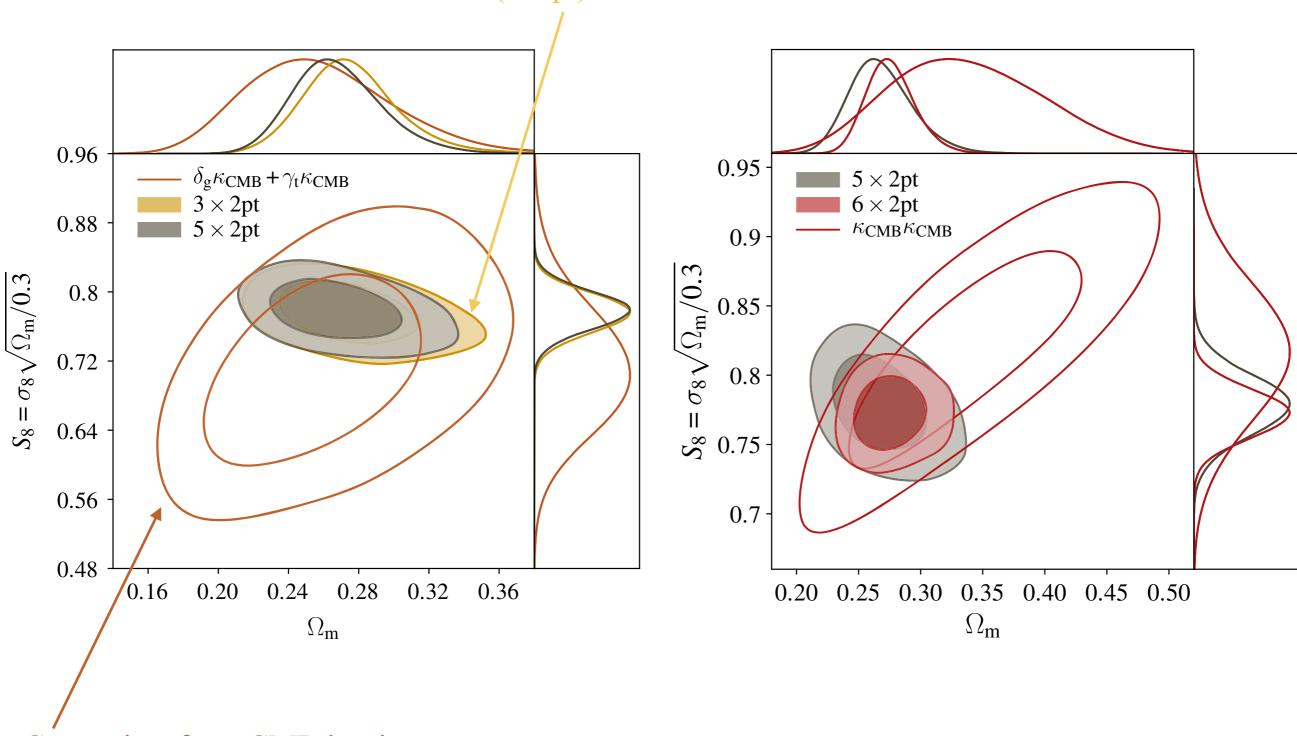
Six 2pt functions = "6x2pt"





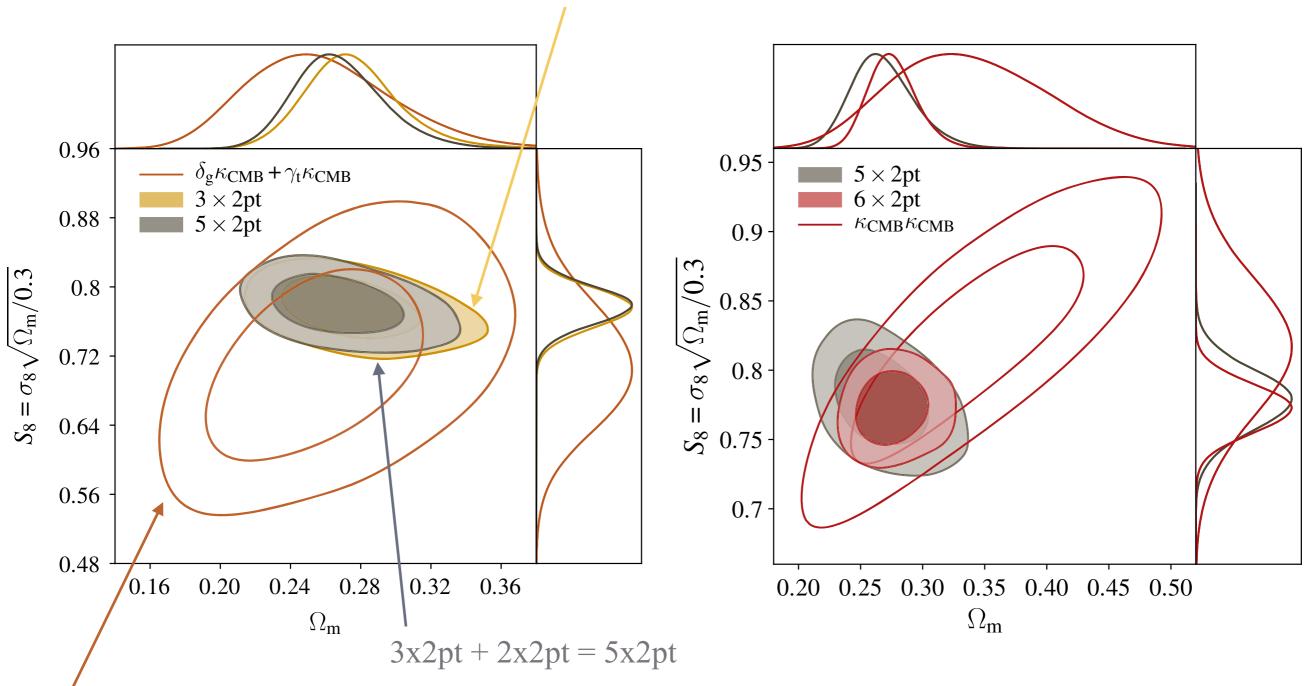




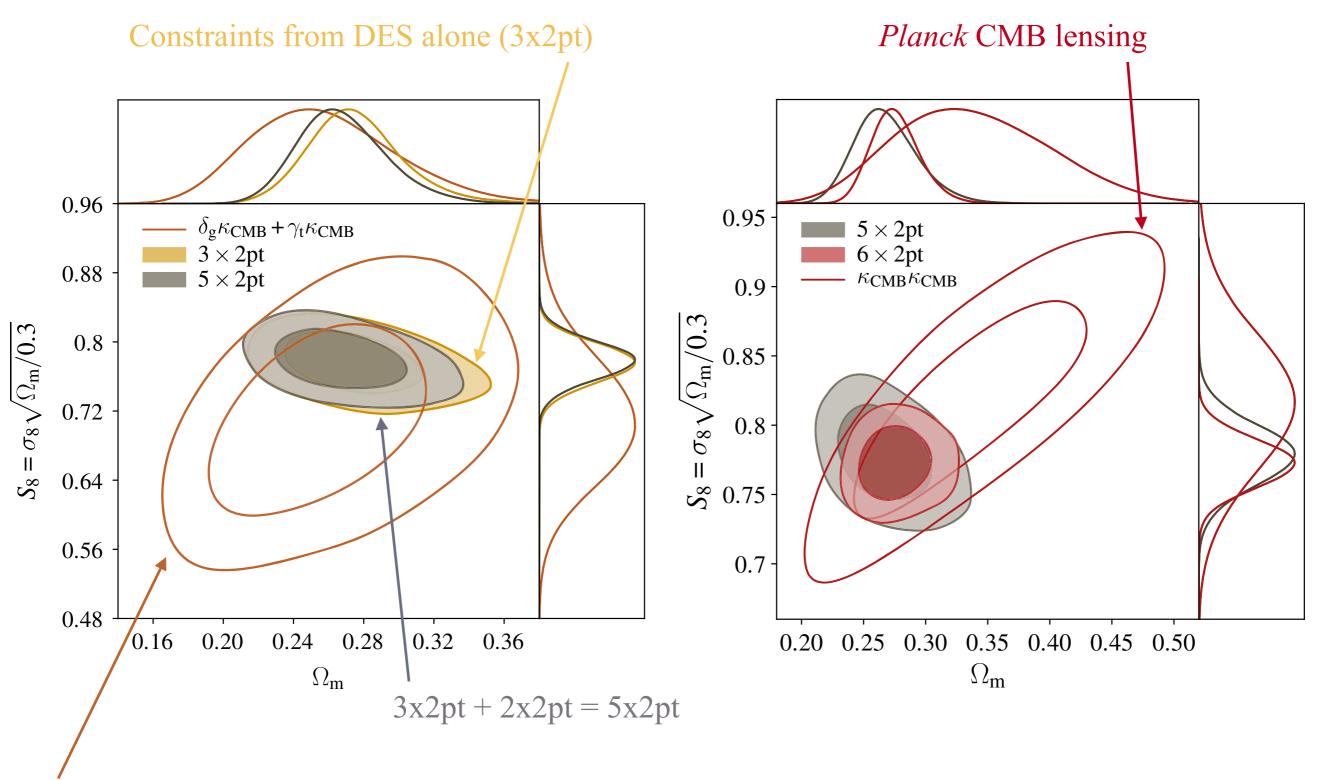


Constraints from CMB lensing cross-correlations (2x2pt)

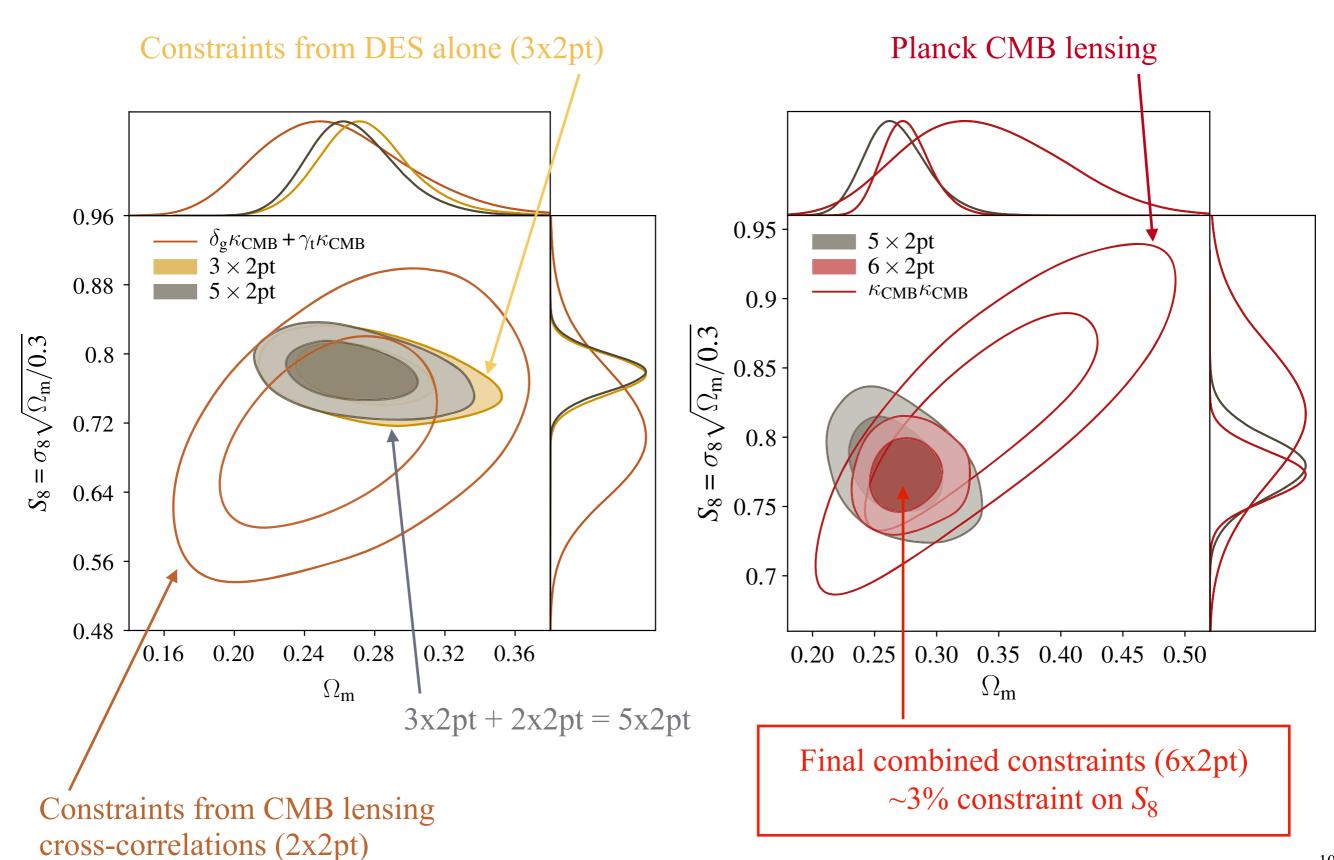


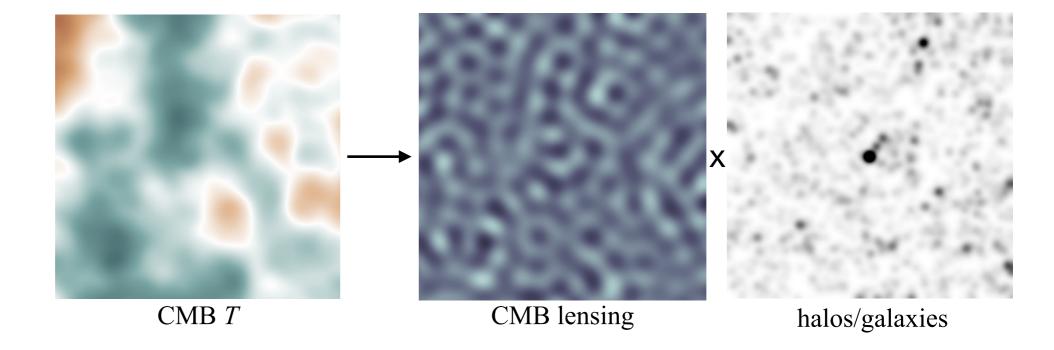


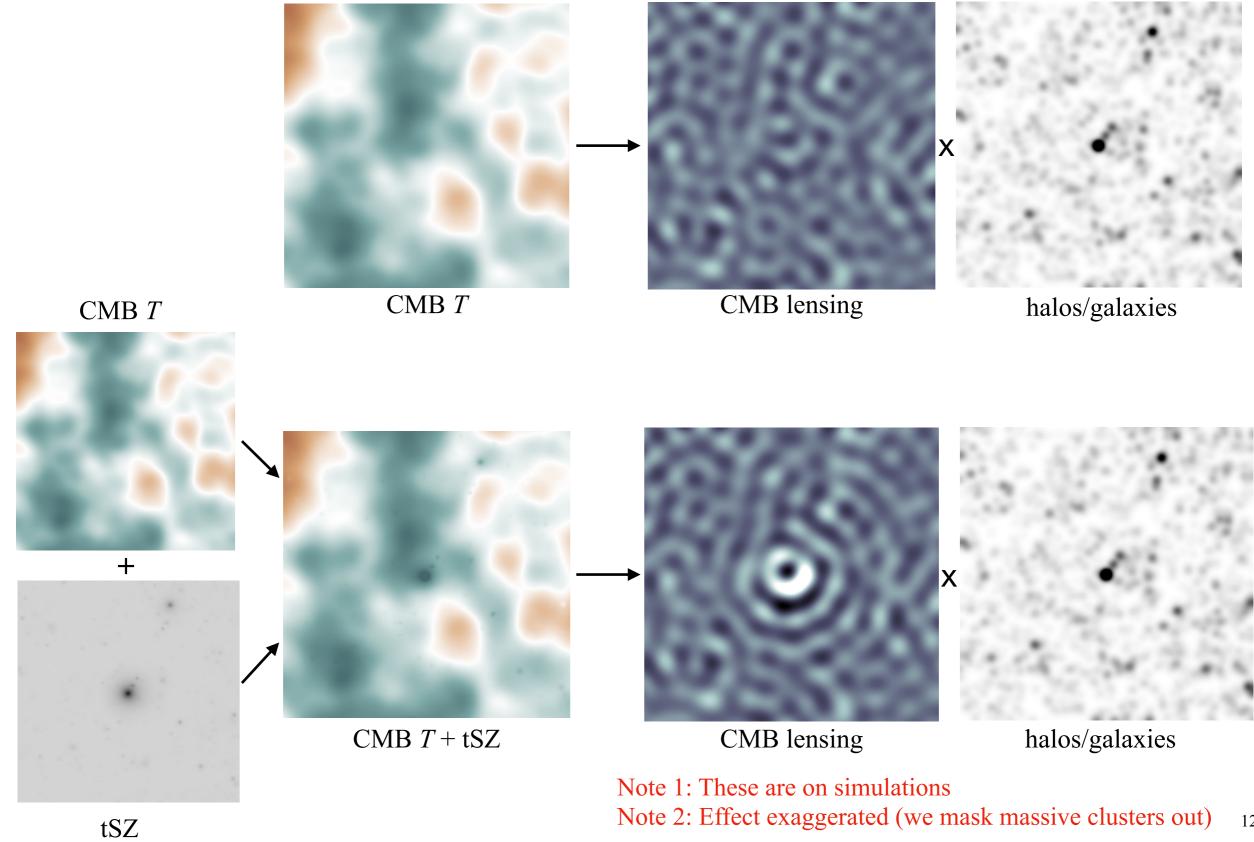
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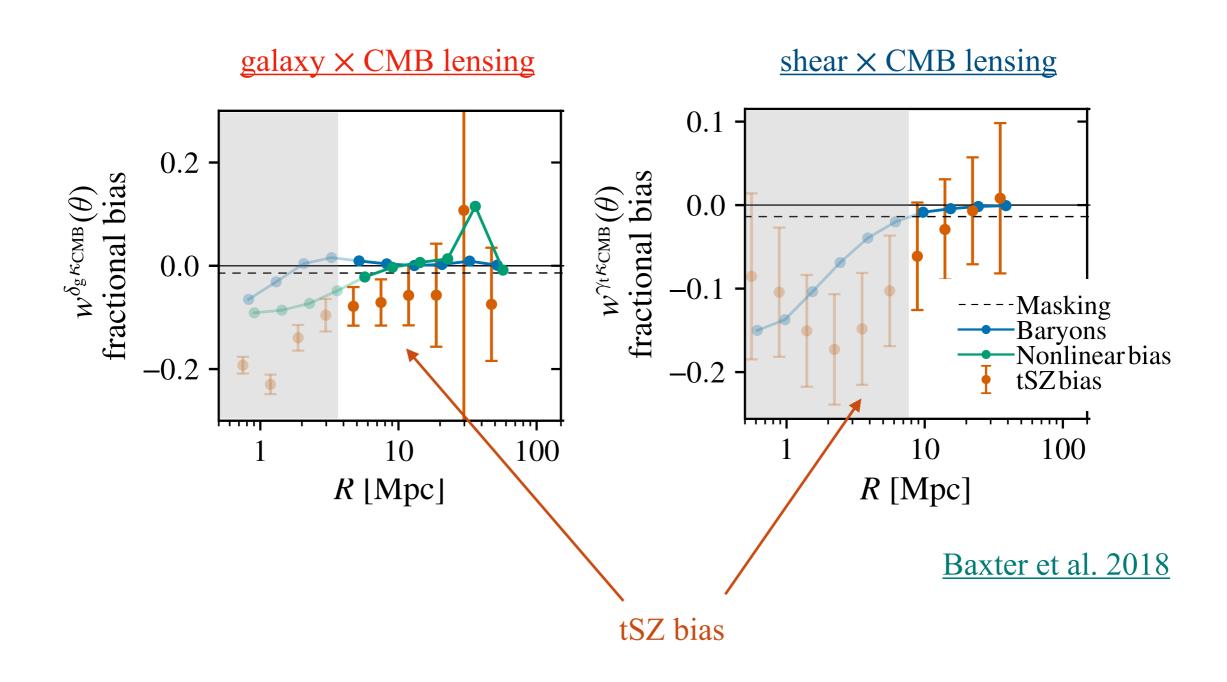
Constraints from CMB lensing cross-correlations (2x2pt)



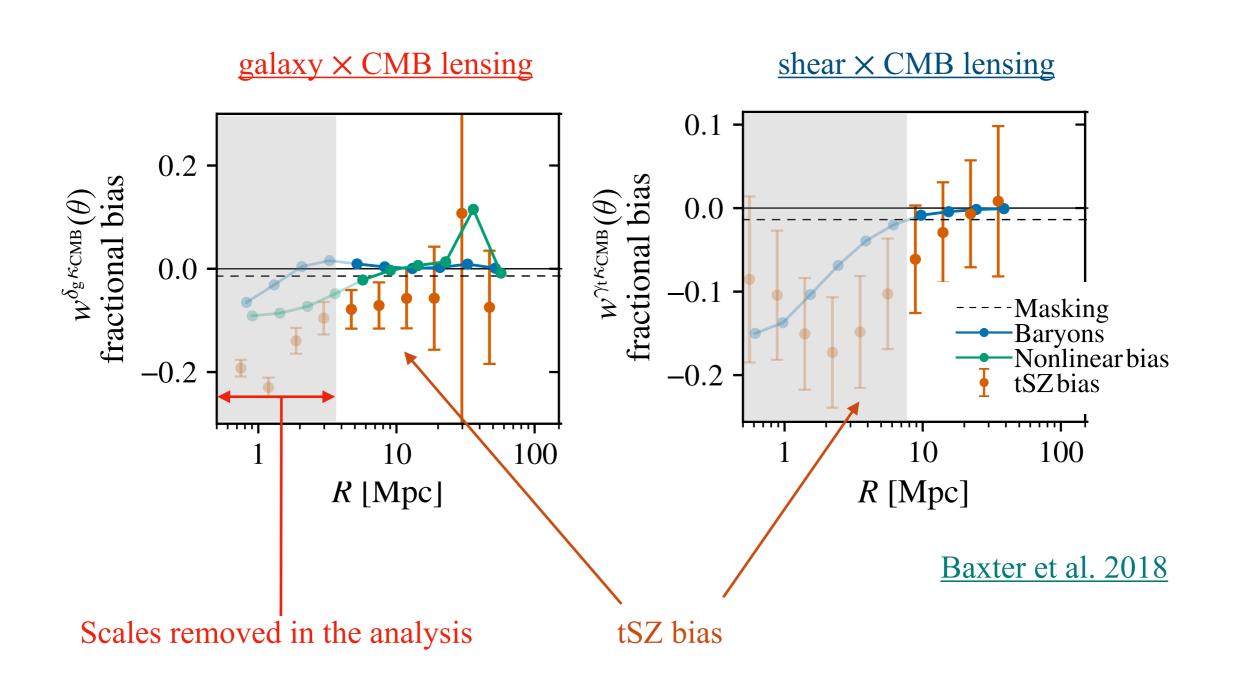


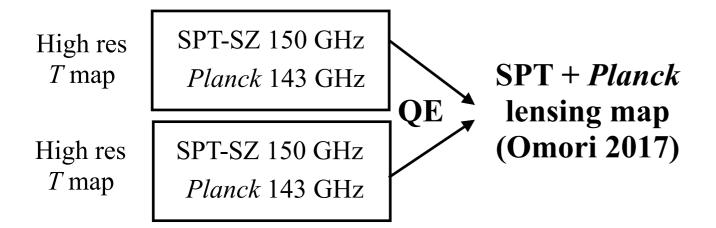


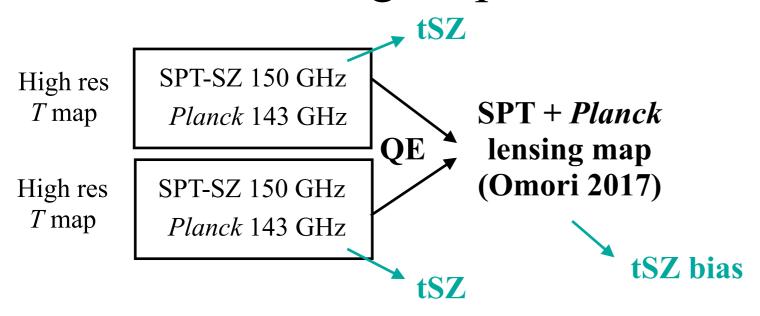
tSZ bias was the main driver for our choice of angular scale cuts in DES-Y1 analysis

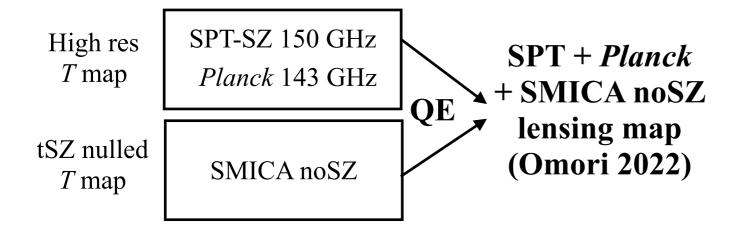


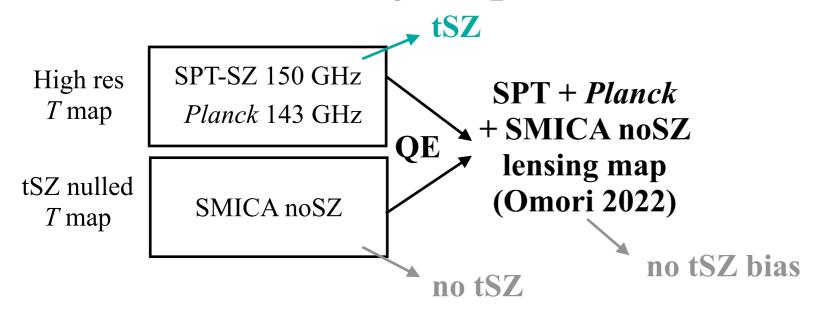
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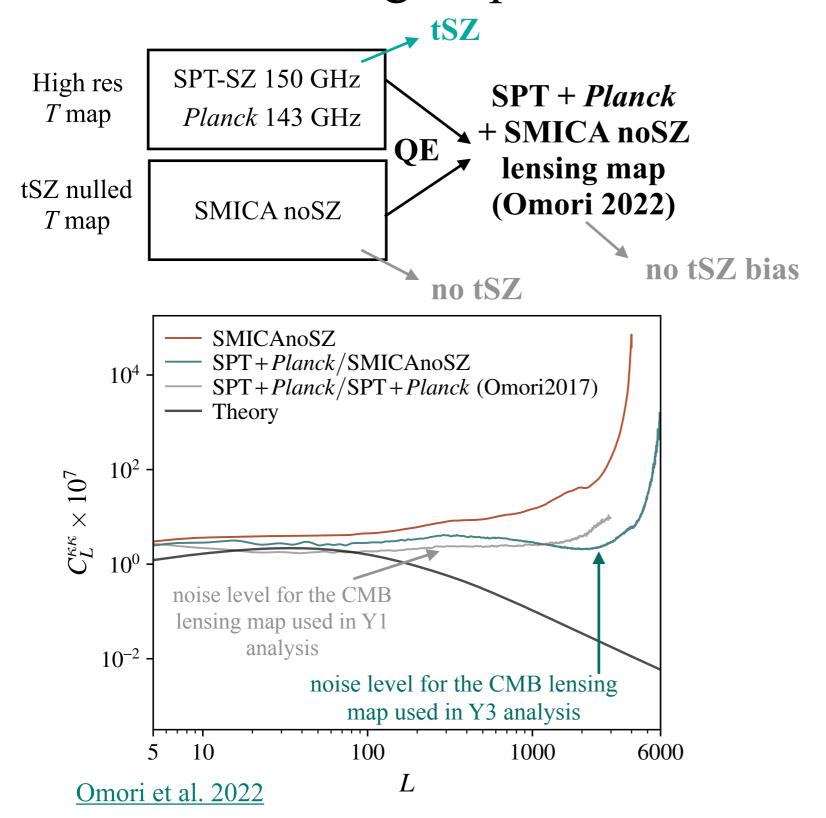


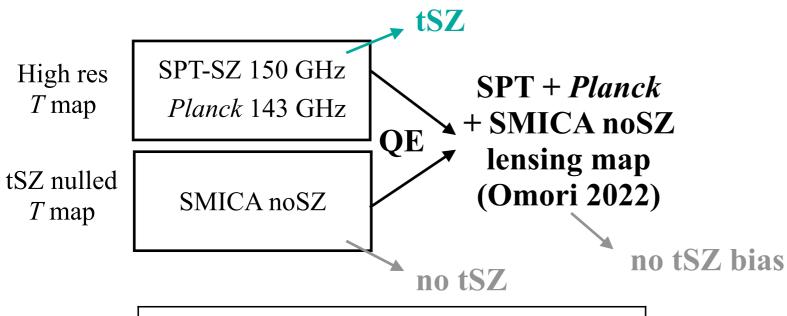


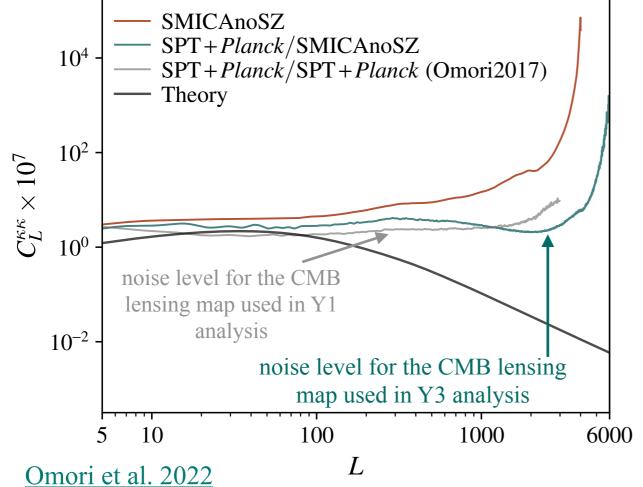




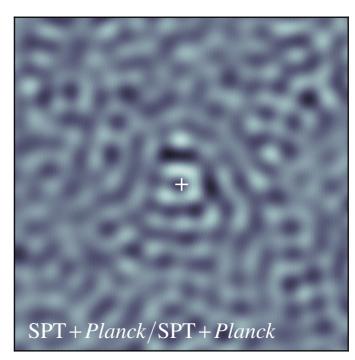




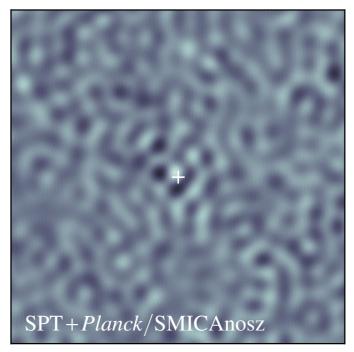




CMB lensing maps stacked at the location of clusters



Similar to the CMB lensing map used in Y1



New CMB lensing map used in Y3

Omori et al. 2022

Omori et al. 2022 10 4 $L^{1.5}C_L^{\kappa\kappa}\times 10^4$ 3 1000 2000 4000 L Planck 2018 Omori 2017 SPT+*Planck*/SMICAnoSZ 0 100 1000 10 6000 L

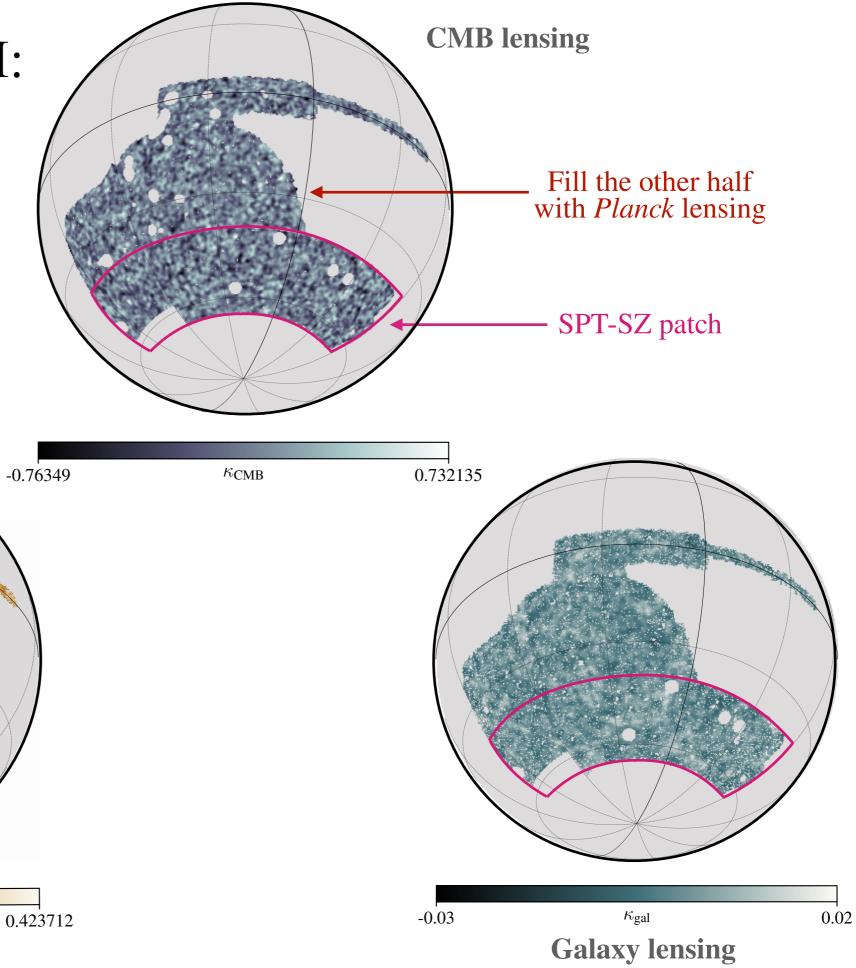
CMB lensing auto-spectrum

Y3 improvement II: Larger Y3 area

 $\delta_{
m gal}$

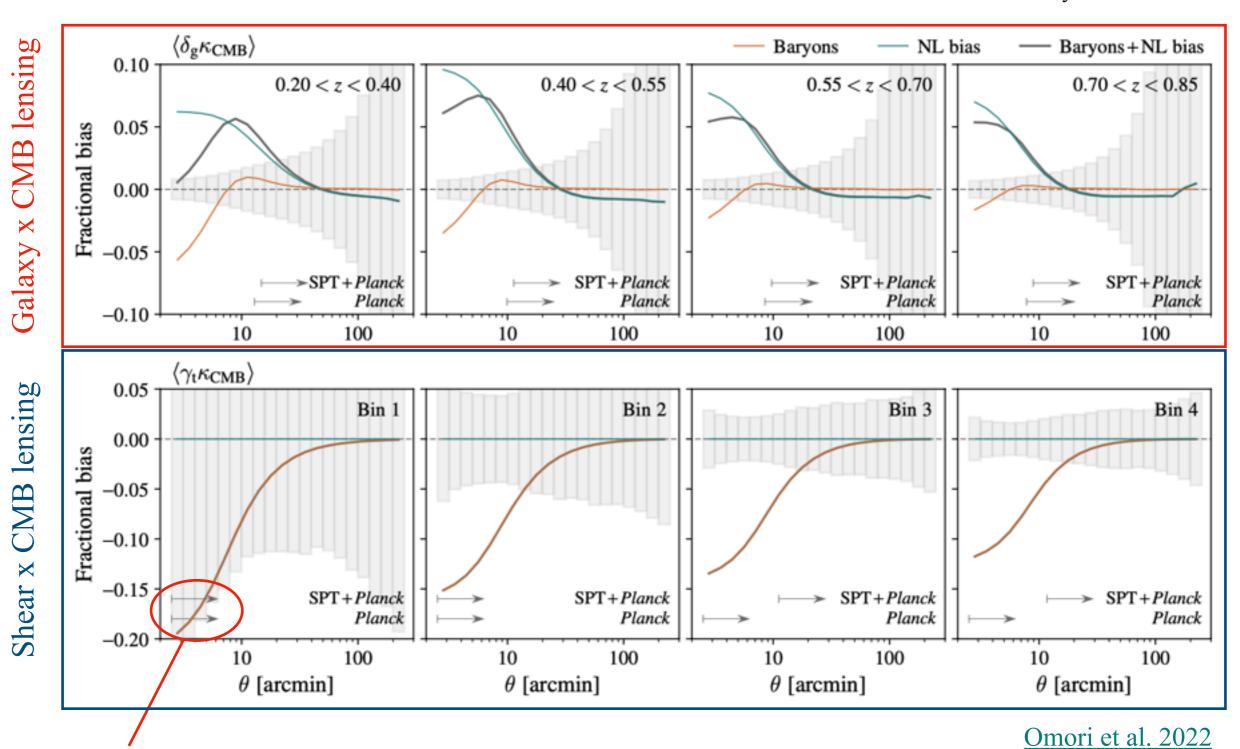
Lens galaxies

-0.808956

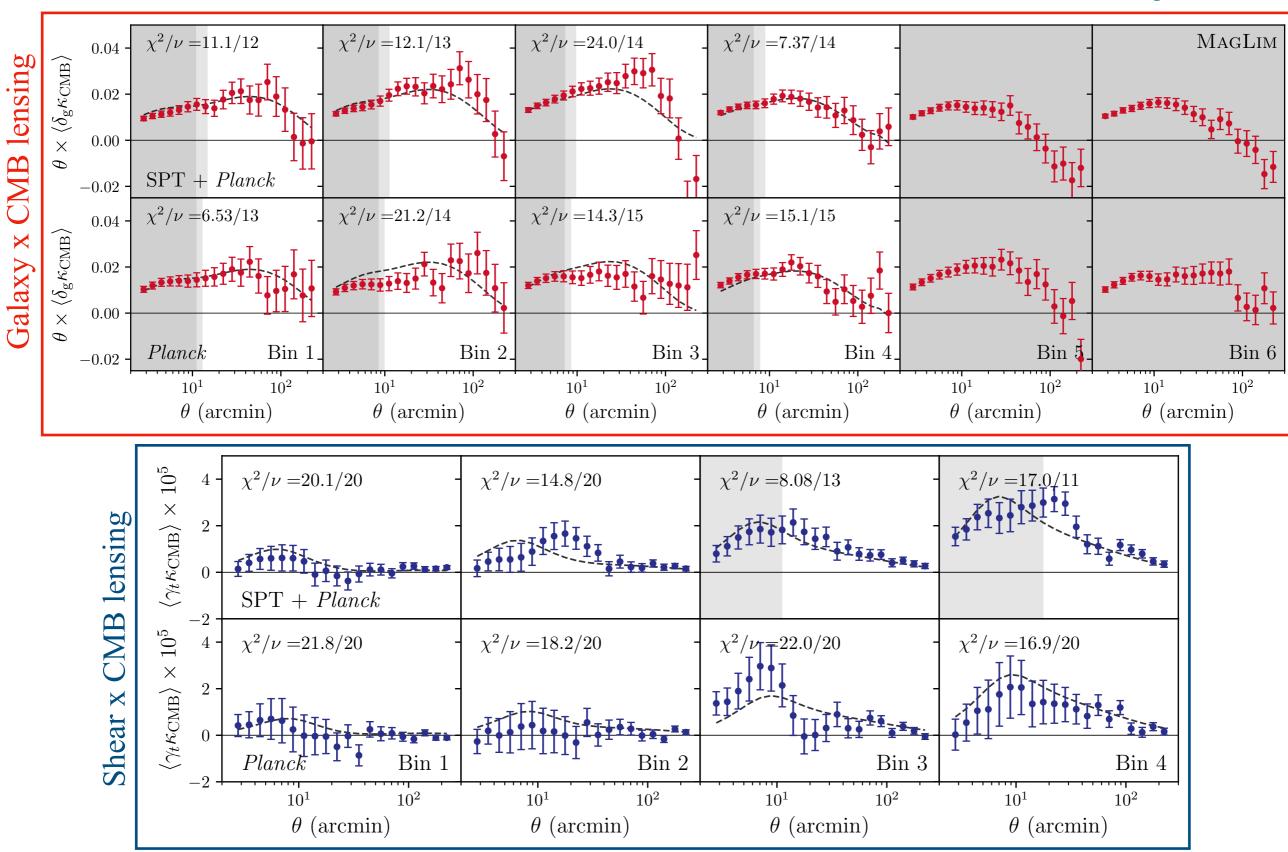


Scale cuts

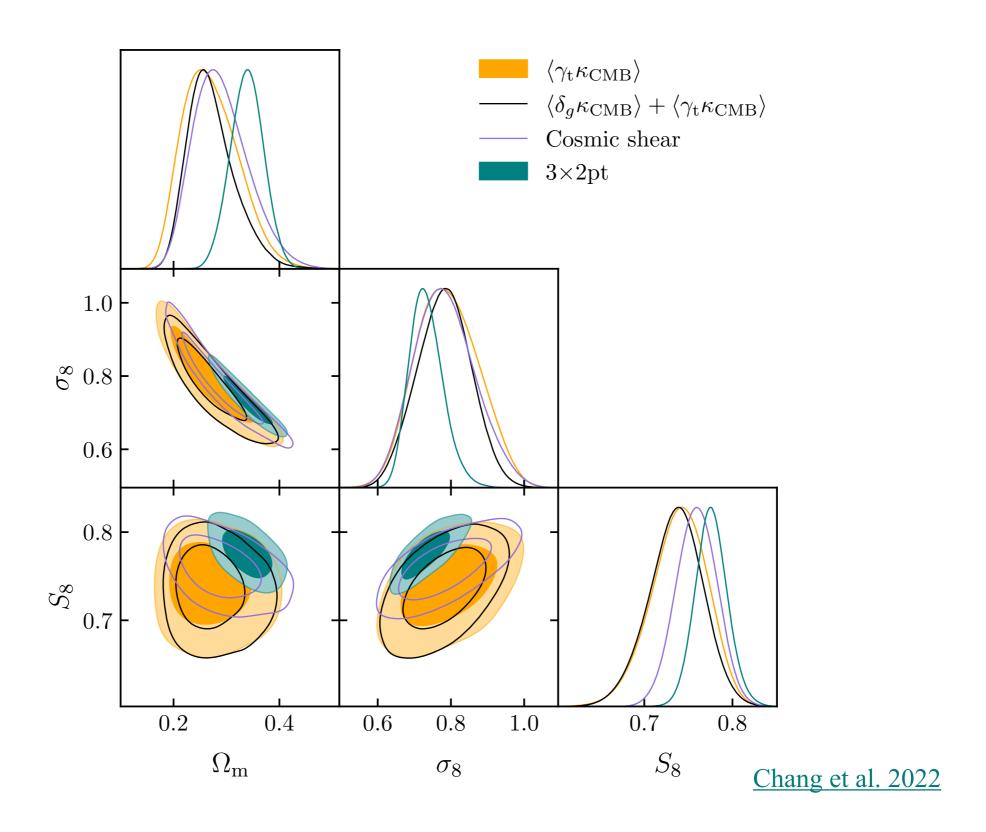
**Errors scaled down by a factor of 10



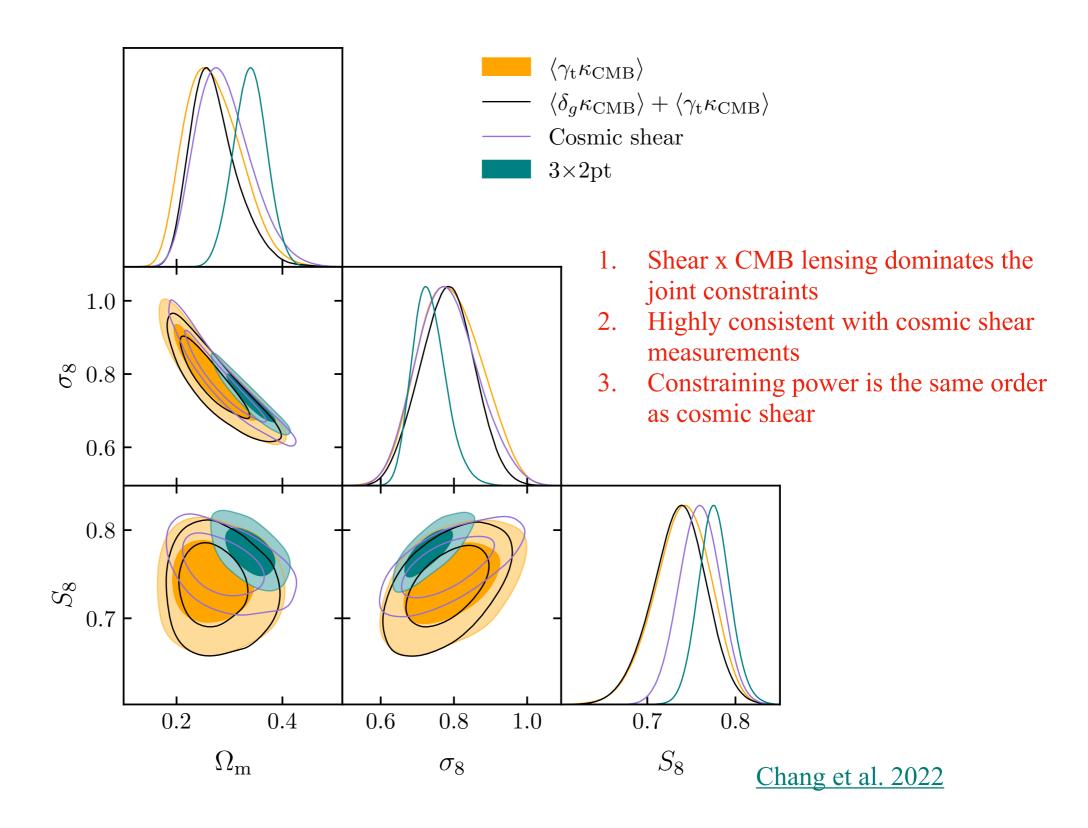
Scales used in the analysis



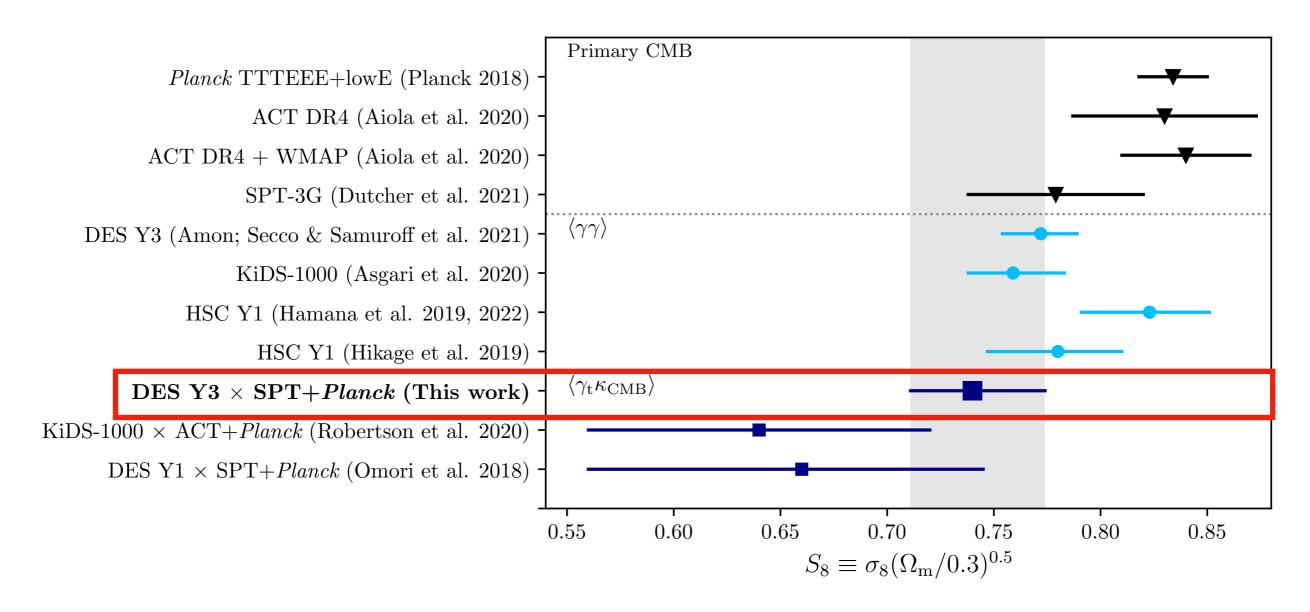
Constraints



Constraints

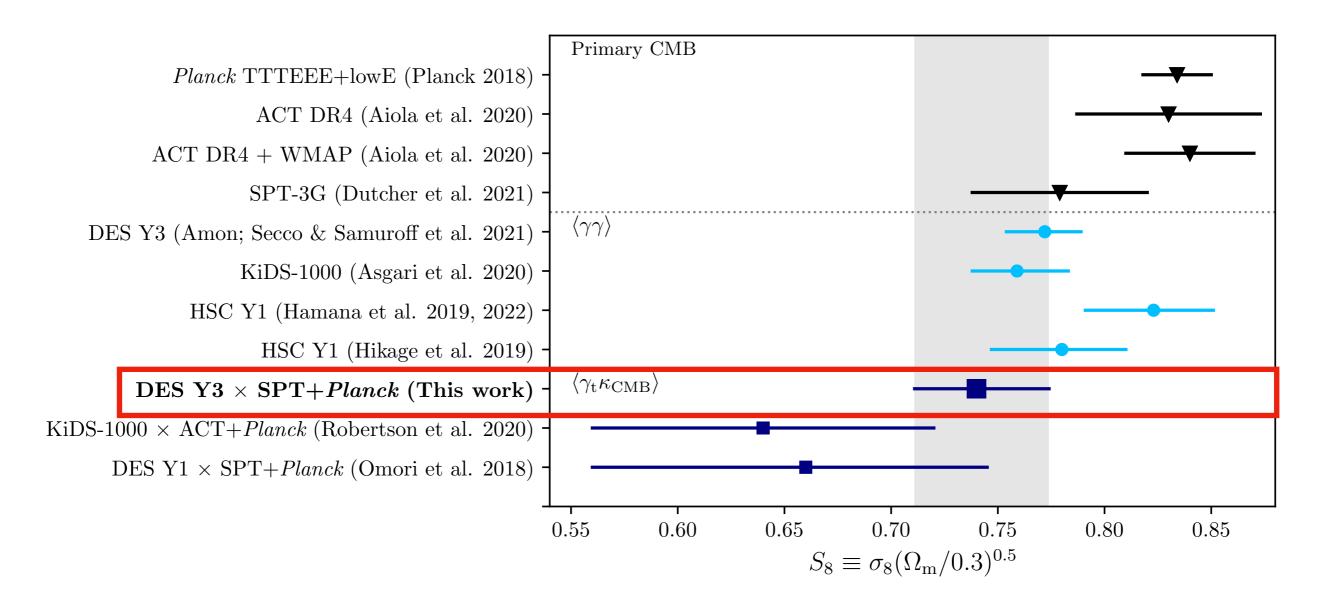


Comparison with other surveys



Chang et al. 2022

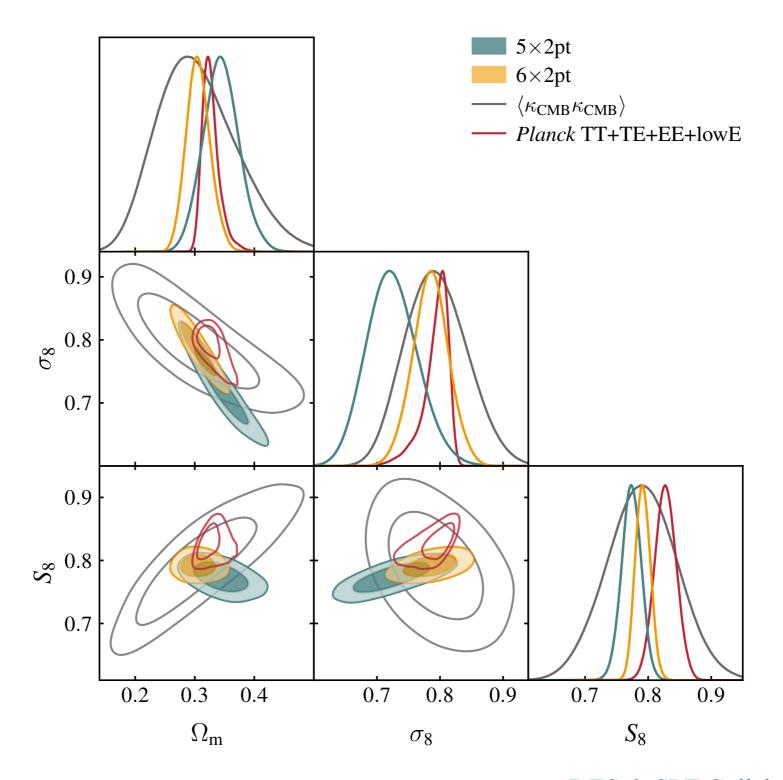
Comparison with other surveys



Chang et al. 2022

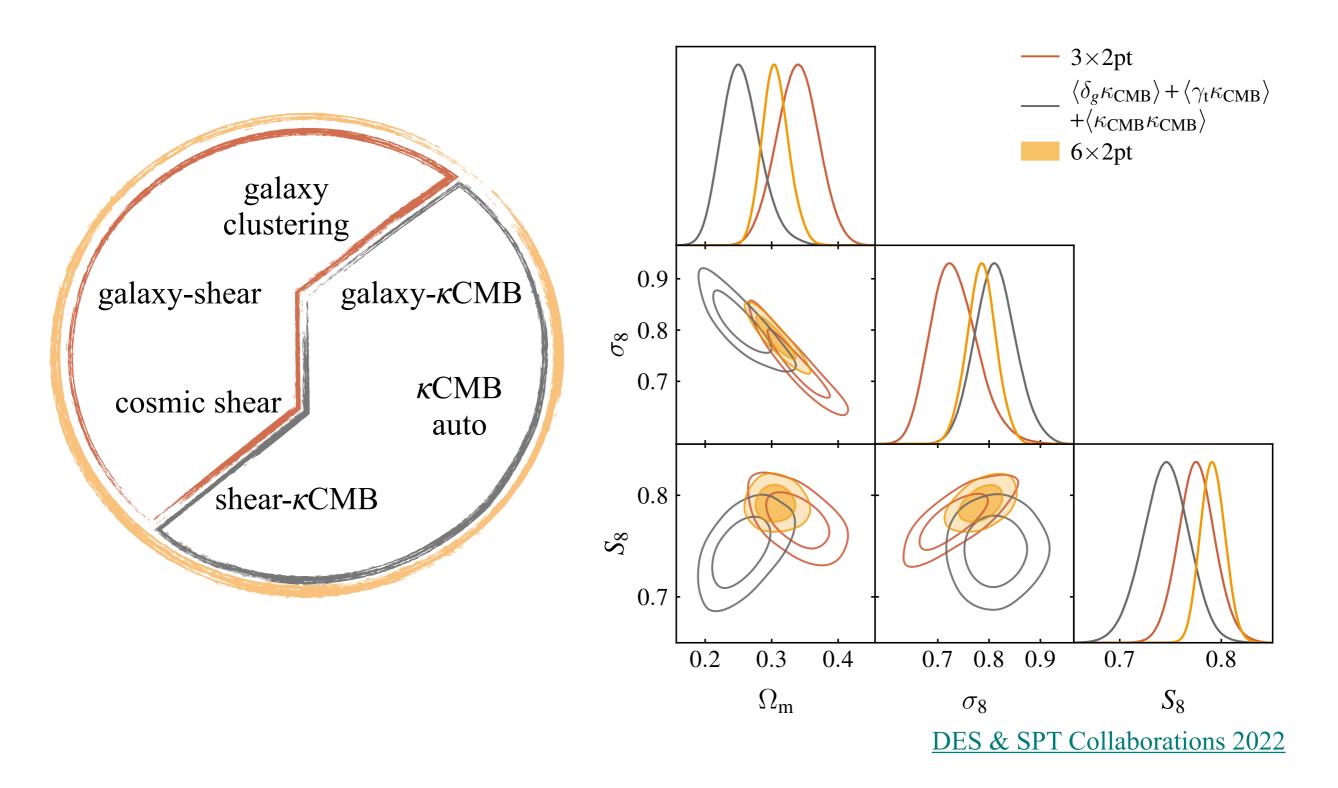
- 1. Factor of ~3 improvement compared to Y1
- 2. 1-sigma consistent with cosmic shear

Main combined results

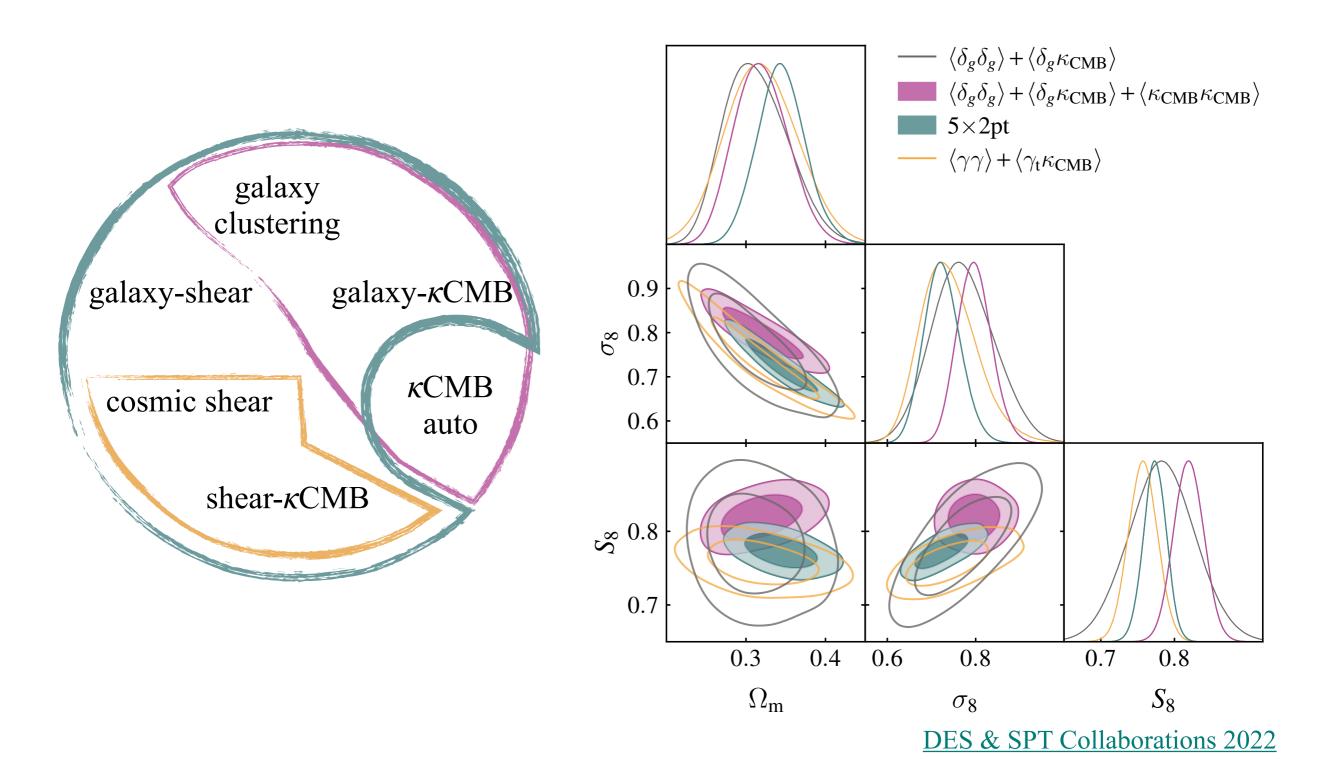


DES & SPT Collaborations 2022

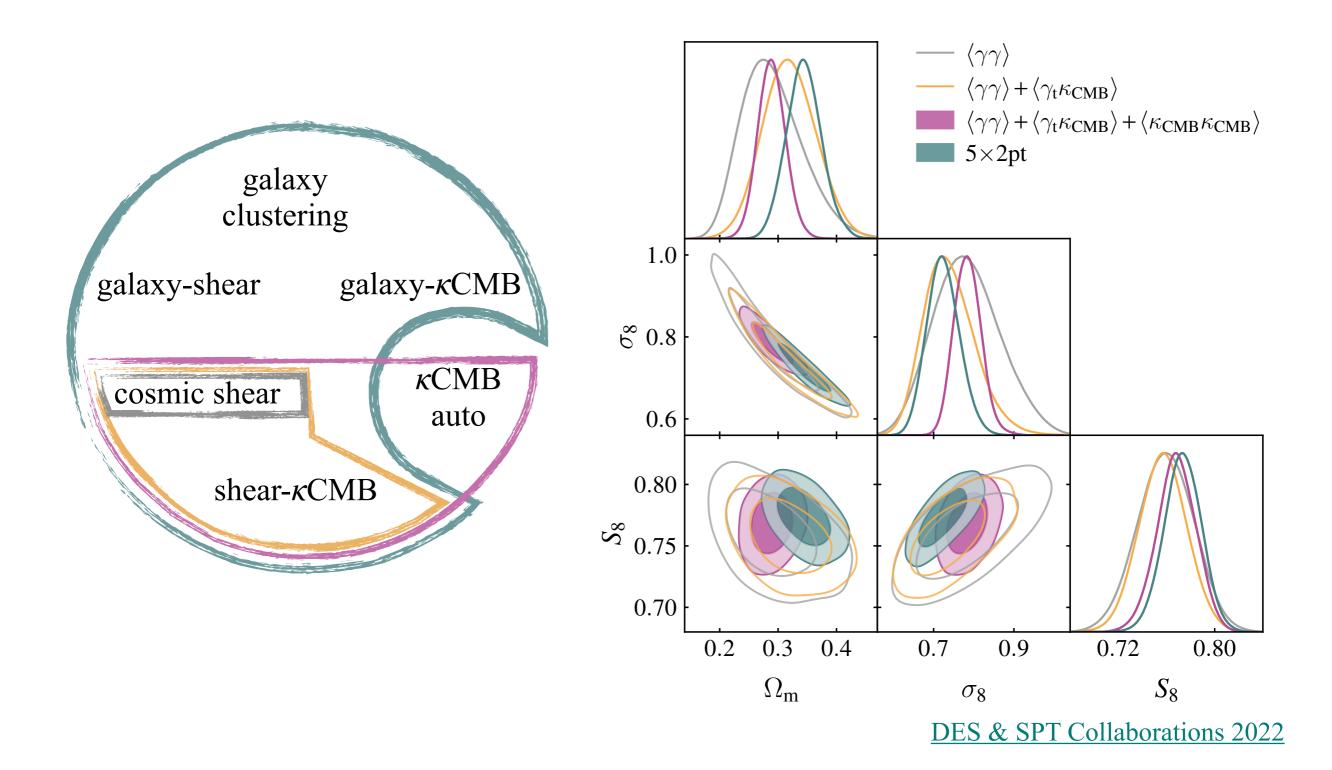
Results: 3x2pt vs "other 3x2pt" vs 6x2pt



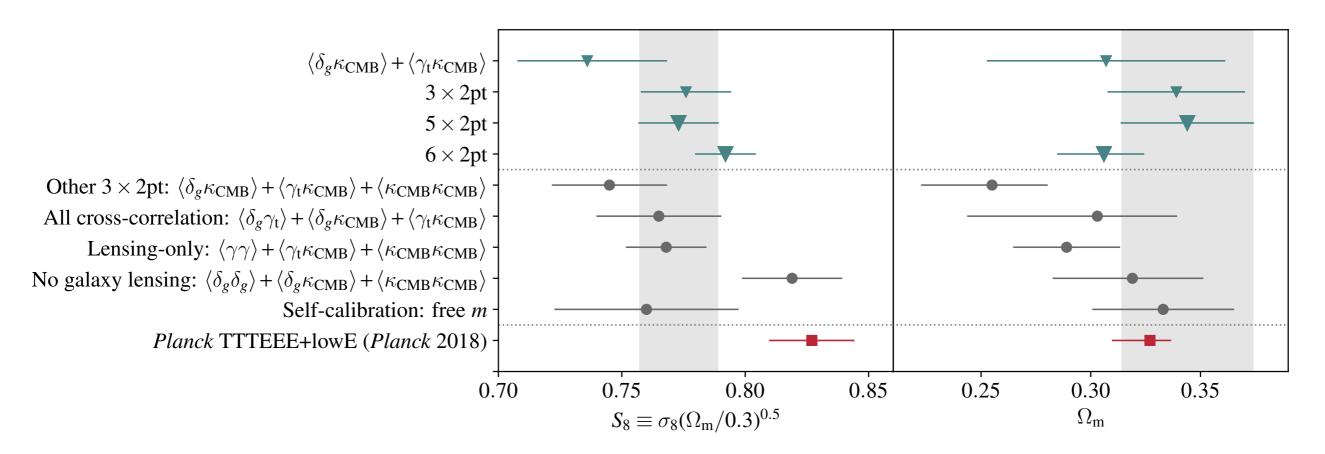
Results: 3x2pt vs "no gal lensing" vs 5x2pt vs "gal lensing"



Results: Lensing only

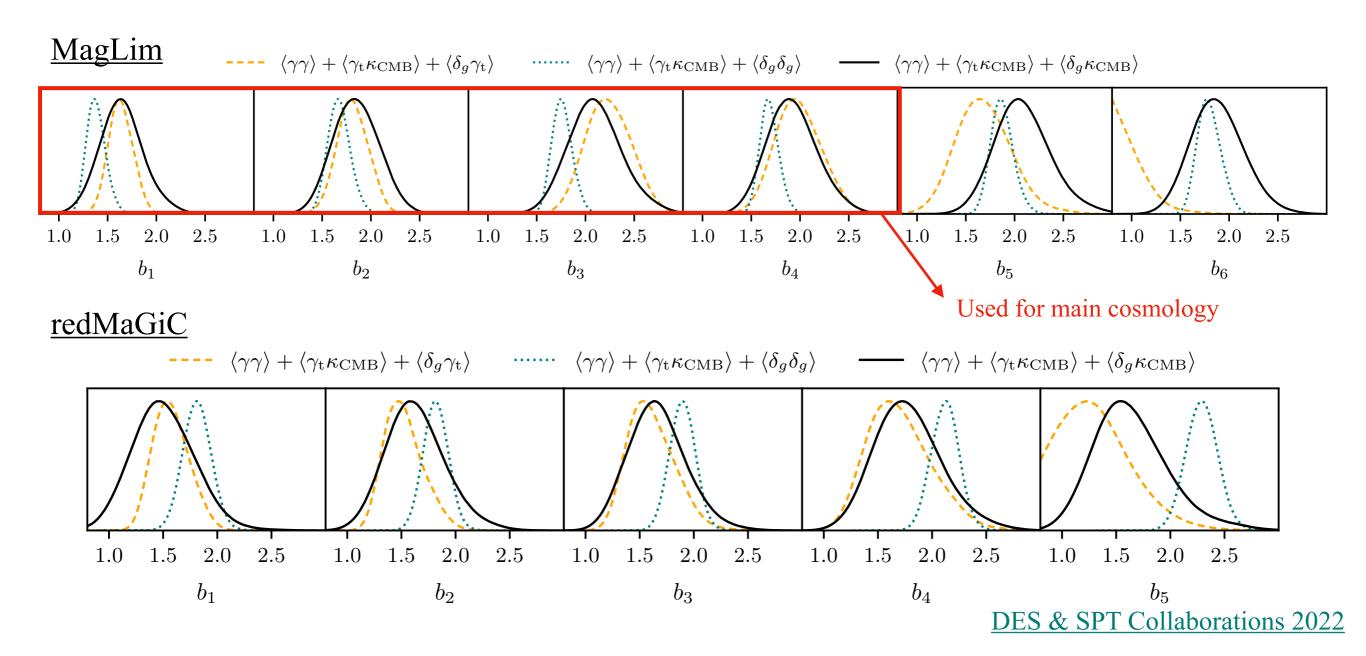


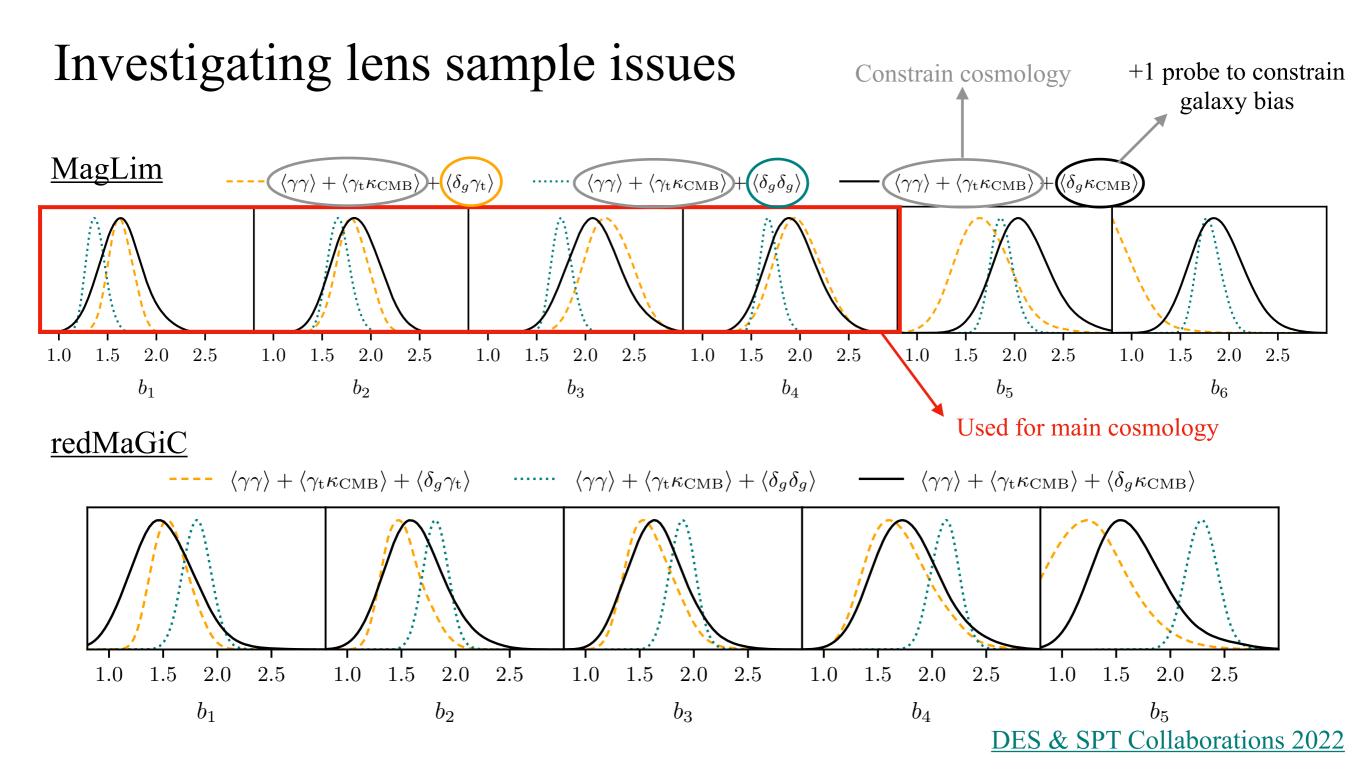
Main combined results

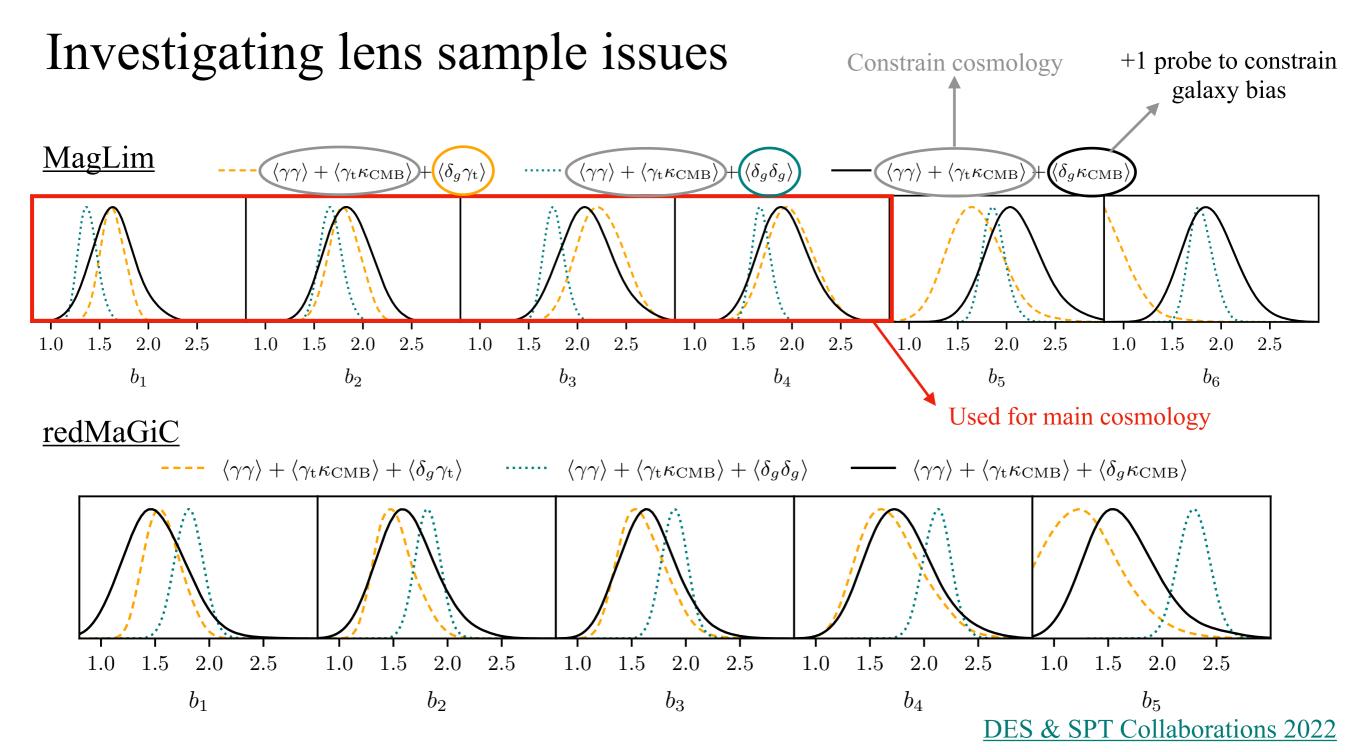


DES & SPT Collaborations 2022

Investigating lens sample issues





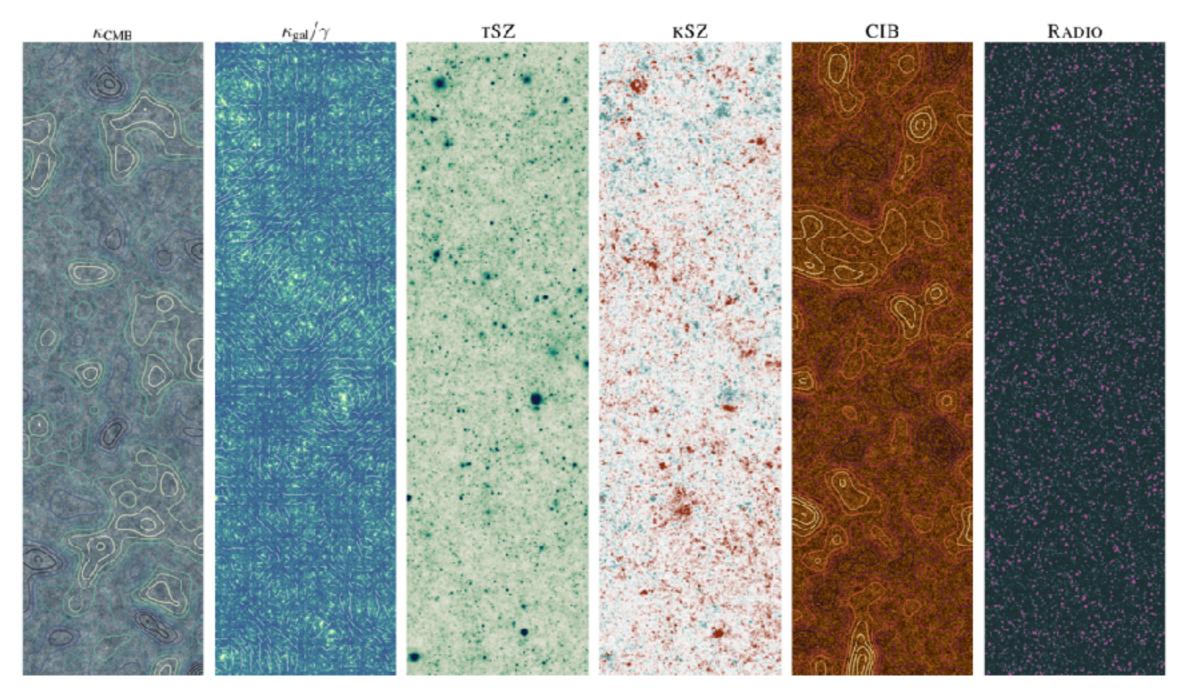


Our constraints are mild so we do not have a definitive answer, but...

- For MagLim, bias values agree more with gg-lensing except the last two bin where the results match better with clustering.
- For redMaGiC, bias values agree more with gg-lensing.

Part I summary

- DES uses galaxy position/shear information to extract cosmology (3×2pt)
- By cross-correlating with CMB lensing maps we get an addition three 2pt functions (i.e. 6×2pt).
- Significant improvements were made:
 - Improvement of the CMB lensing map (tSZ nulling)
 - Y3 coverage
- shear × CMB lensing dominates the constraing power over galaxy × CMB lensing.
- Cosmological constraints from combing the two cross-correlation probes is competetive with cosmic shear measurements (so we can use it to test for systematic errors in DES data).
- The combined cosmological constraints are consistent with *Planck* primary constraints.



Part II: MultiDark Planck 2 Synthetic Sky Simulation

MDPL2

MDPL2

The MultiDark Planck 2 simulation belongs to the series of MultiDark simulations with Planck cosmology. It is kin to the MDPL simulation, with the same box size, cosmological parameters and particle resolution, but a different initial seed.

If you are in doubt whether to use MDPL or MDPL2, we recommend to use MDPL2, since there will be more data products available for this simulation in the future (e.g. Rockstar-catalogues).

Please give proper Credits when using data from this simulation.



https://www.cosmosim.org/cms/simulations/mdpl2/

- Publicly available dark matter only *N*-body simulation.
- Rockstar halo catalogs, semi-analytic galaxy catalogs are available online.

Configuration	
Box size	$1 h^{-1}$ Gpc
N_{part}	3840^{3}
Mass resolution	$1.51 \times 10^9 \ h^{-1} \mathrm{M}_{\odot}$
Force resolution	$\sim 15 h^{-1} \text{kpc}$ (at high z)
	$\sim 8 h^{-1} \text{kpc} \text{ (at low } z)$
Initial redshift	120
$N_{ m snap}$	130

CMB components

Implemented CMB secondaries:

- Thermal Sunyaev Zel'dovich effect (tSZ)
- Kinetic Sunyaev Zel'dovich effect (kSZ)
- Cosmic infrared background (CIB) and IR sources
- Radio galaxies
- CMB lensing from ray-tracing
- galactic foregrounds from PySM3

LSS components

• Lens galaxies:

BYO HOD: various groups have used MDPL2 to implement galaxies including BOSS & DESI. Some people are working on implementing DES-Y3 MagLim sample. Also have DES-Y1/DES-Y3/LSST-Y1 Poisson sampled galaxies.

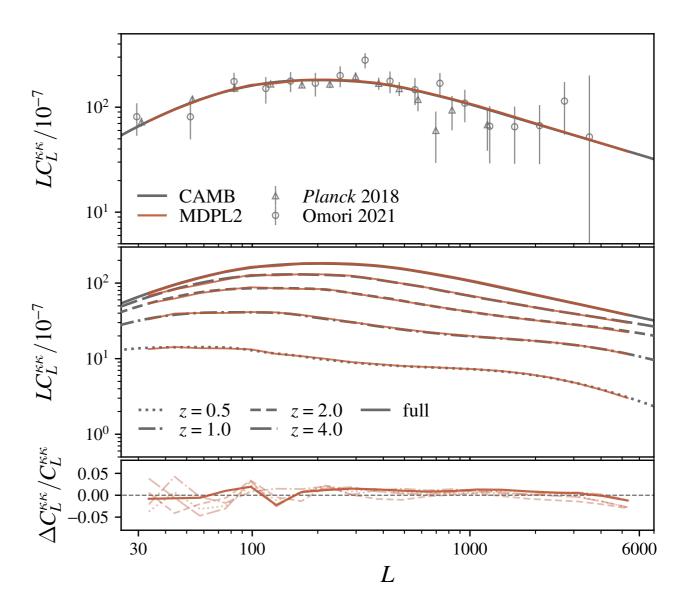
• Source galaxies:

Shear signal from ray-tracing, with noise added by randomly rotating e_1 , e_2 from data or σ_e values (includes NLA IA). Currently have DES-Y1/DES-Y3/LSST-Y1 mock catalogs.

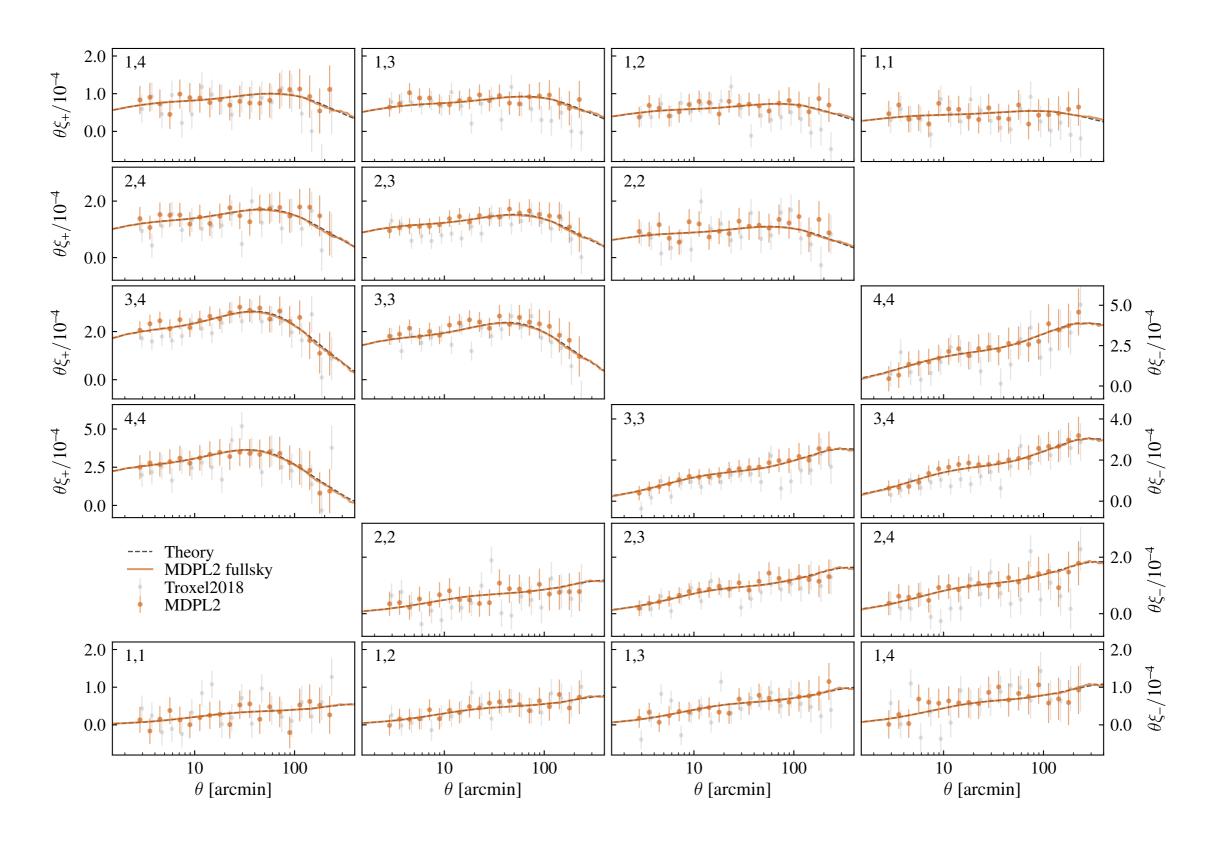
Lensing components

To produce the lensing maps:

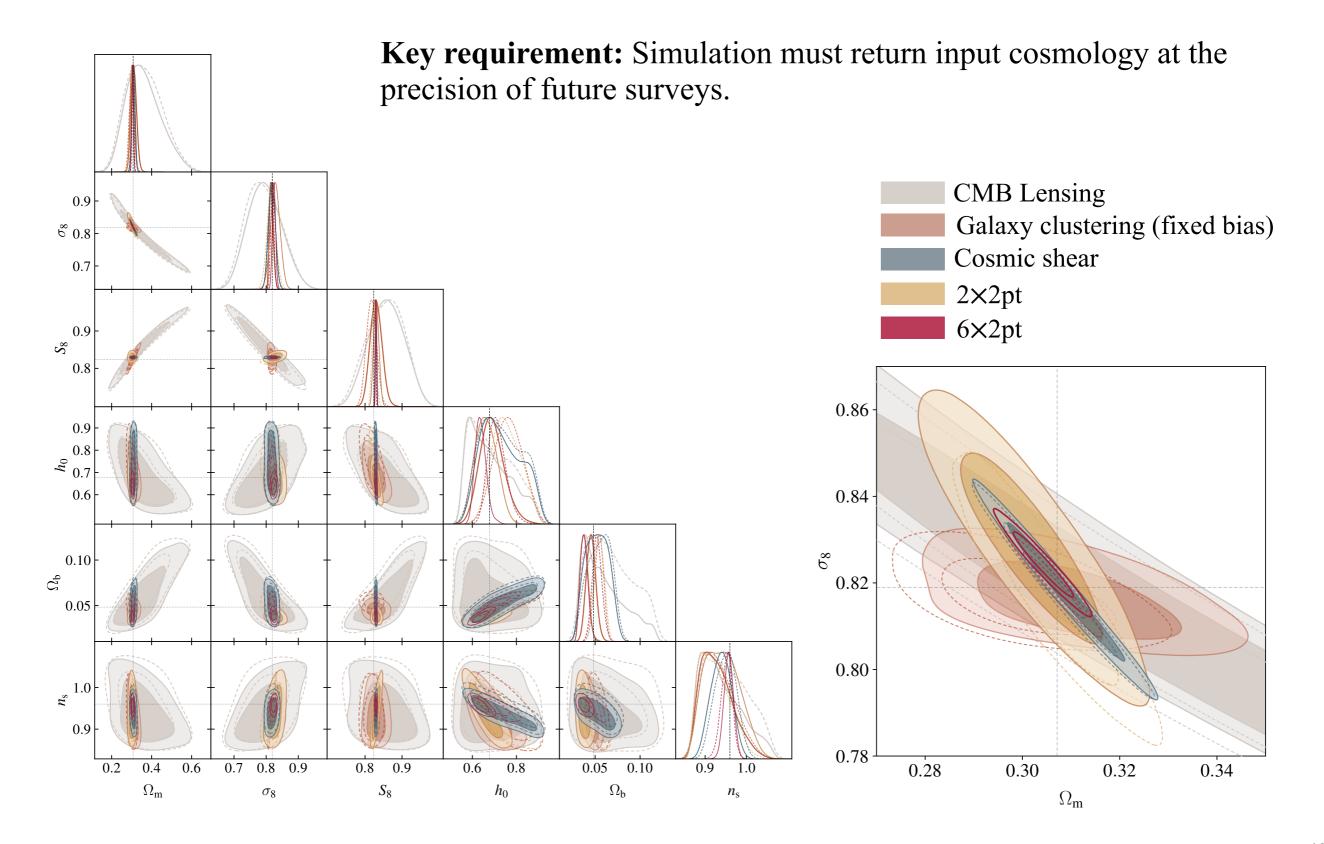
- 1. Project all the particles onto HEALPix shells of width of 25 Mpc/h.
- 2. Apply rotation every 1Gpc/h to avoid repeating structure.
- 3. Run raytracing at *N*side=16384.
- 4. Both galaxy and CMB lensing are processed up to z=8.6, and a Gaussian component is added to CMB lensing (to cover 8.6 < z < 1100).



Lensing components



Lensing components



Implementation: tSZ

The tSZ map is generated using the MDPL2

Rockstar halo catalog and using the Mead2020

model, which is calibrated against the

BAHAMAS simulation (McCarthy 2016).

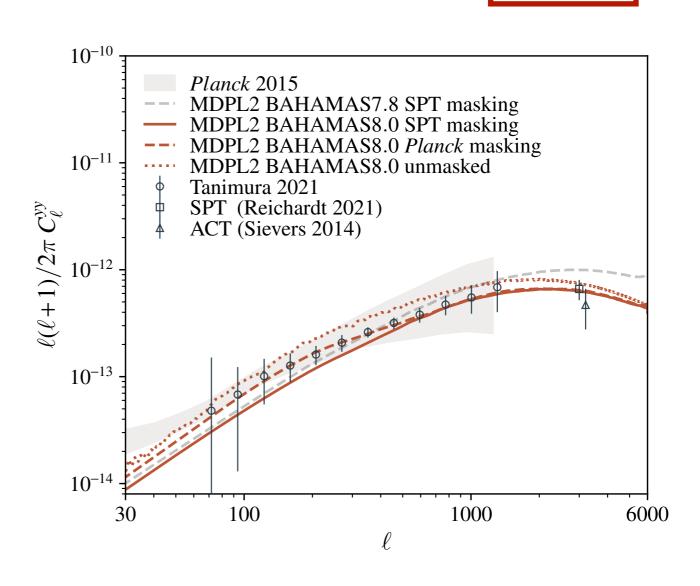
$$y(\hat{n}) = \frac{\sigma_{\rm T}}{m_{\rm e}c^2} \int_{\rm LOS} dl \ P_{\rm e}$$

$$P_{\rm e}^{\rm bnd}(M_{\rm vir},r) = \frac{\rho_{\rm gas}^{\rm bnd}(M_{\rm vir},r)}{m_{\rm p}\mu_{\rm e}} k_{\rm B}T_{\rm gas}(M_{\rm vir},r)$$

$$\rho_{\text{gas}}^{\text{bnd}}(M_{\text{vir}}, r) = \rho_0 \left[\frac{\ln(1 + r/r_{\text{s}})}{r/r_{\text{s}}} \right]^{1/\Gamma - 1}$$

Currently using the $T_{AGN} = 10^{8.0}$ K model as the default (see e.g. <u>Tröester2021</u>).

Parameter	10 ^{7.6} [K]	10 ^{7.8} [K]	10 ^{8.0} [K]
ϵ_0	-0.1002	-0.1065	-0.1253
$oldsymbol{\epsilon}_1$	-0.0456	-0.1073	-0.0111
Γ	1.1647	1.1770	1.1966
M_0	13.1949	13.5937	14.2480
α	0.7642	0.8471	1.0314
$oldsymbol{eta}$	0.6	0.6	0.6
$\log(T_{\rm w,0}/K)$	6.6762	6.6545	6.6615
$T_{ m w,1}$	-0.5566	-0.3652	-0.0617



Implementation: kSZ

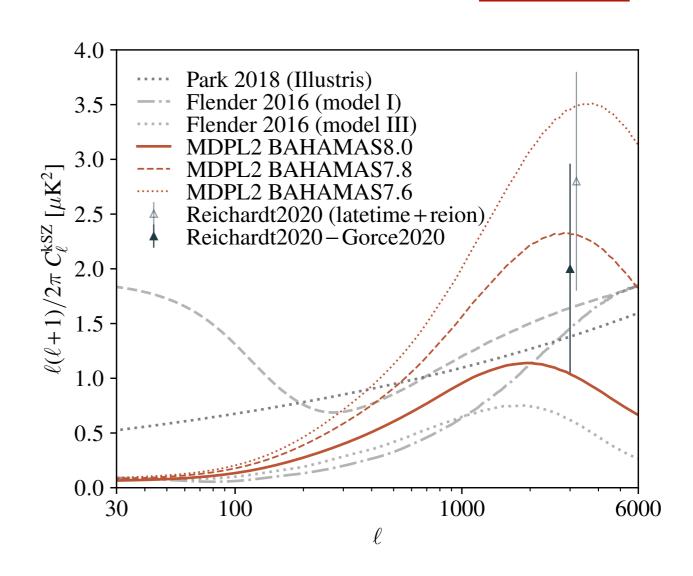
The kSZ map is similarly generated using the MDPL2 Rockstar halo catalog and the velocity information from particles and following the Mead2020 model.

$$\left(\frac{\Delta T}{T}\right)_{\text{kSZ}} = -\frac{\sigma_{\text{T}}}{c} \int_{\text{LOS}} dl \ n_{\text{e}} \ v_{\text{LOS}}$$

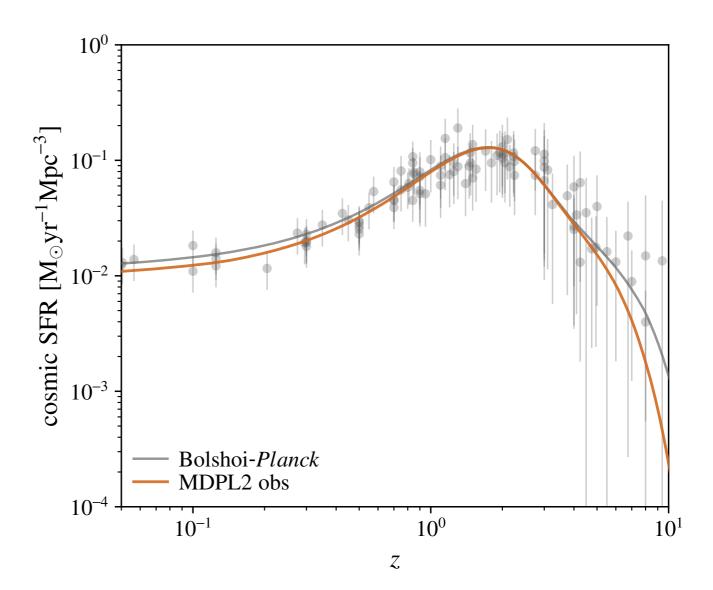
$$n_{\rm e} = \frac{\rho_{\rm gas}^{\rm bnd}(M_{\rm vir}, r)}{m_{\rm p}\mu_{\rm e}}$$

$$\rho_{\text{gas}}^{\text{bnd}}(M_{\text{vir}}, r) = \rho_0 \left[\frac{\ln(1 + r/r_{\text{s}})}{r/r_{\text{s}}} \right]^{1/\Gamma - 1}$$

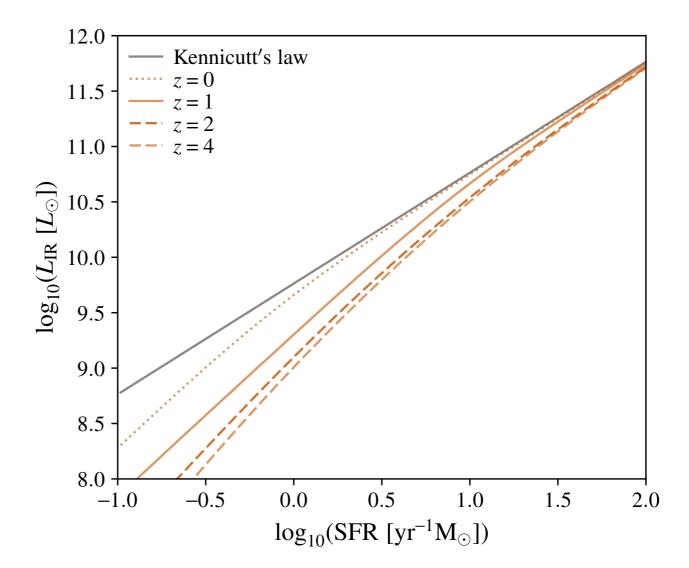
Parameter	10 ^{7.6} [K]	10 ^{7.8} [K]	10 ^{8.0} [K]
ϵ_0	-0.1002	-0.1065	-0.1253
ϵ_1	-0.0456	-0.1073	-0.0111
Γ	1.1647	1.1770	1.1966
M_0	13.1949	13.5937	14.2480
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- 1. Start from Rockstar halos.
- 2. Apply UniverseMachine (get M_*/SFR).



- 1. Start from Rockstar halos.
- 2. Apply UniverseMachine (get M_*/SFR).
- 3. Apply Kennicutts' law (get L_{IR}).



$$L_{IR} = \frac{\text{SFR}}{K_{IR} + K_{UV} 10^{-IRX(M_*)}}$$

$$\log_{10} IRX = 1.37 \times \log_{10} \left(\frac{M_*}{10^{9.63}}\right)$$
(Bouwens2020)

(Donevski2020)

- 1. Start from Rockstar halos.
- 2. Apply UniverseMachine (get M_*/SFR).
- 3. Apply Kennicutts' law (get L_{IR}).
- 4. Use empirical fitting relations to obtain $M_{\rm dust}$ and $T_{\rm dust}$.

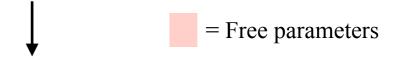
$$\frac{M_{\rm dust}}{M_*} = \frac{M_{\rm mol}}{M_*} \times Z_{\rm gas}$$

(Tacconi2020)

$$\frac{M_{\text{mol}}}{M_*} = A + B \times (\log(1+z))^2 + D \times \log_{10}(M_* - 10.7)$$

(<u>Hunt2016</u>)

$$Z_{\text{gas}} = -0.14\log_{10}(\text{SFR}) + 0.37\log_{10}(M_*) + 4.82$$



$$T_{\rm d} = A_{\rm d} \left(\frac{L_{\rm IR}}{M_{\rm dust}}\right)^{1/(4+\beta_{\rm d})} \qquad \beta_{\rm d} = \frac{\zeta_{\rm d} \times a}{b + c \times T_{\rm d}}$$

- 1. Start from Rockstar halos.
- 2. Apply UniverseMachine (get M_*/SFR).
- 3. Apply Kennicutts' law (get L_{IR}).
- 4. Use empirical fitting relations to obtain $M_{\rm dust}$ and $T_{\rm dust}$.
- 5. Compute SED for individual sources

(Donevski2020)

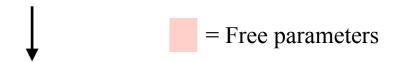
$$\frac{M_{\text{dust}}}{M_*} = \frac{M_{\text{mol}}}{M_*} \times Z_{\text{gas}}$$

(Tacconi2020)

$$\frac{M_{\text{mol}}}{M_*} = A + \frac{B}{B} \times (\log(1+z))^2 + D \times \log_{10}(M_* - 10.7)$$

(<u>Hunt2016</u>)

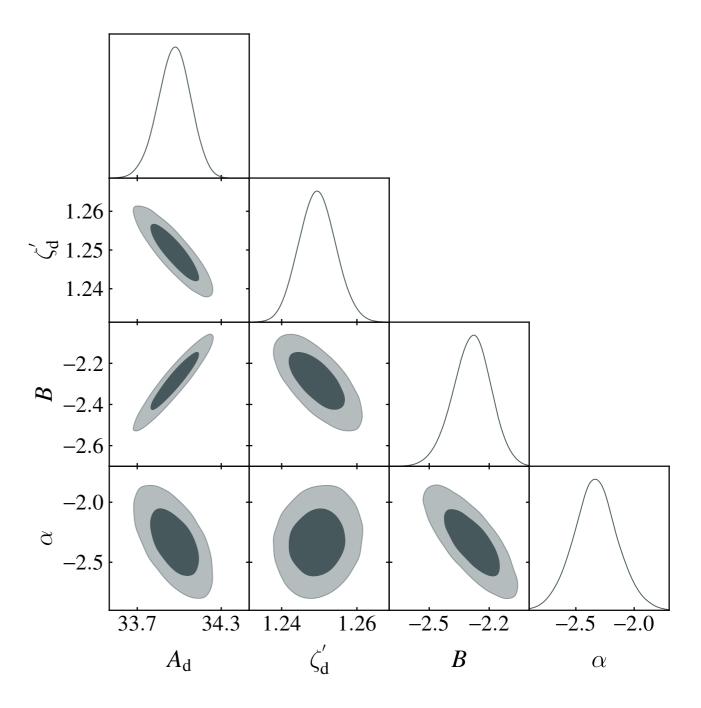
$$Z_{\text{gas}} = -0.14\log_{10}(\text{SFR}) + 0.37\log_{10}(M_*) + 4.82$$



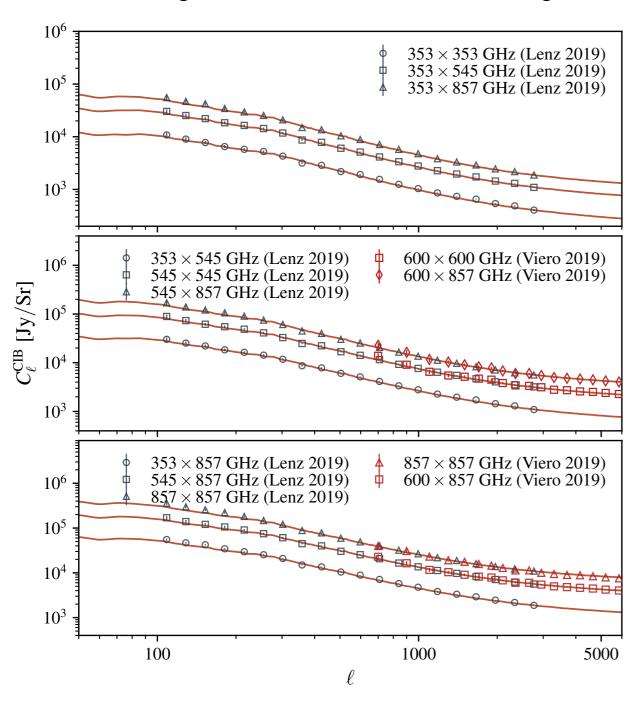
$$T_{\rm d} = A_{\rm d} \left(\frac{L_{\rm IR}}{M_{\rm dust}}\right)^{1/(4+\beta_{\rm d})} \qquad \beta_{\rm d} = \frac{\zeta_{\rm d} \times a}{b+c \times T_{\rm d}}$$

$$\Phi(\nu, T_{\rm d}) = \begin{cases} \left[\exp(\frac{h\nu}{kT_{\rm d}}) - 1 \right]^{-1} \nu^{\beta_{\rm d}+3}, & (\nu \leq \nu') \\ \left[\exp(\frac{h\nu'}{kT_{\rm d}}) - 1 \right]^{-1} \nu'^{\beta_{\rm d}+3} \left(\frac{\nu}{\nu'} \right)^{-\alpha_{\rm d}}, & (\nu > \nu') \end{cases}$$

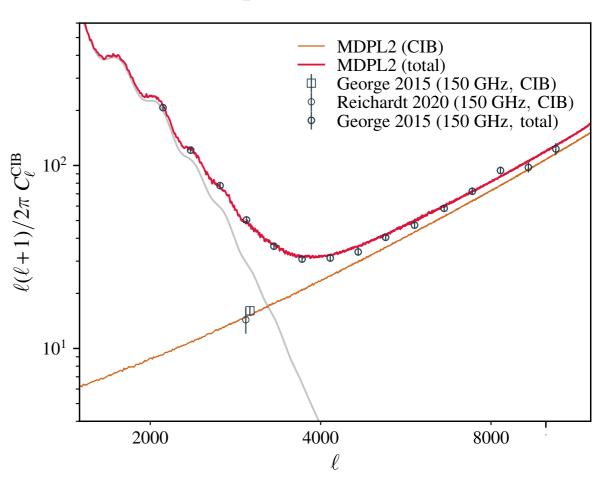
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- 2. Apply UniverseMachine (get M_*/SFR).
- 3. Apply Kennicutts' law (get L_{IR}).
- 4. Use empirical fitting relations to obtain $M_{\rm dust}$ and $T_{\rm dust}$.
- 5. Compute SED for individual sources
- 6. Generate a CIB power spectrum emulator.
- 7. Run MCMC to get best-fit parameters that match with Lenz2019 CIB maps.

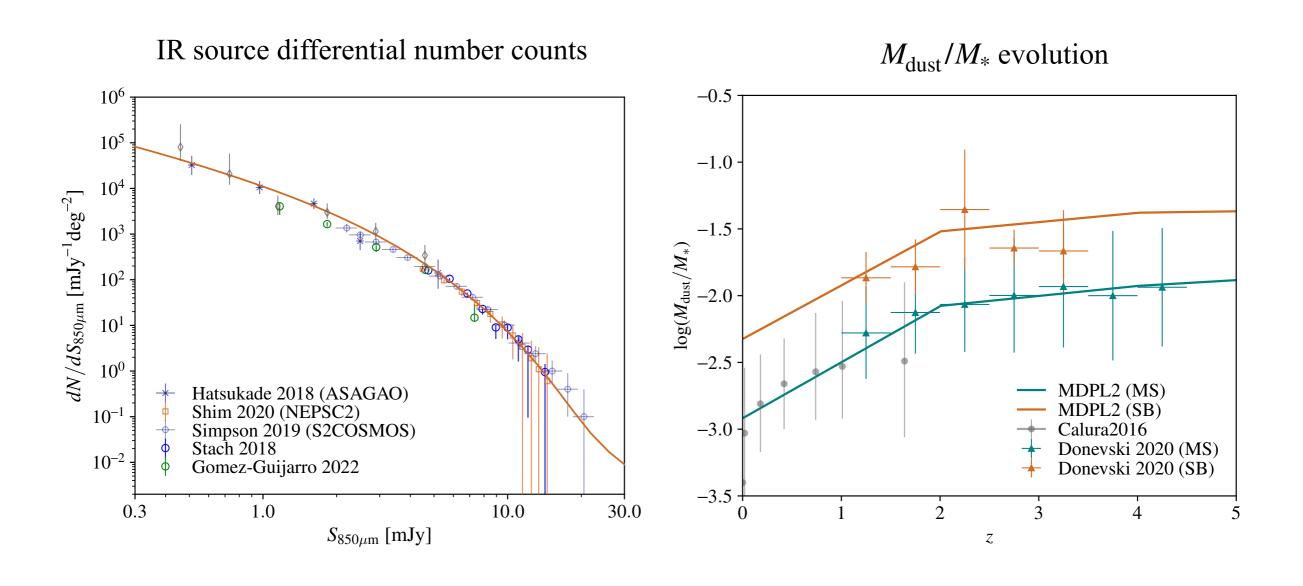


CIB auto-spectrum at *Planck/Herchel* frequencies



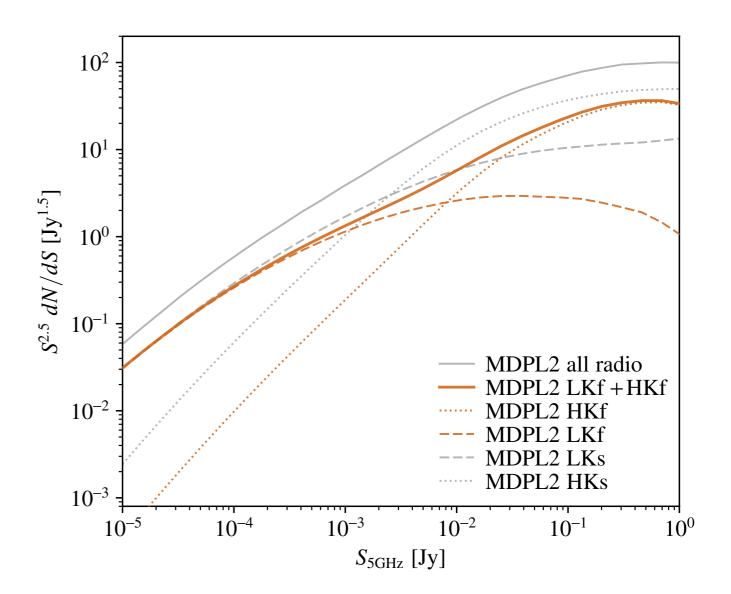
CIB auto-spectrum at SPT 150 GHz





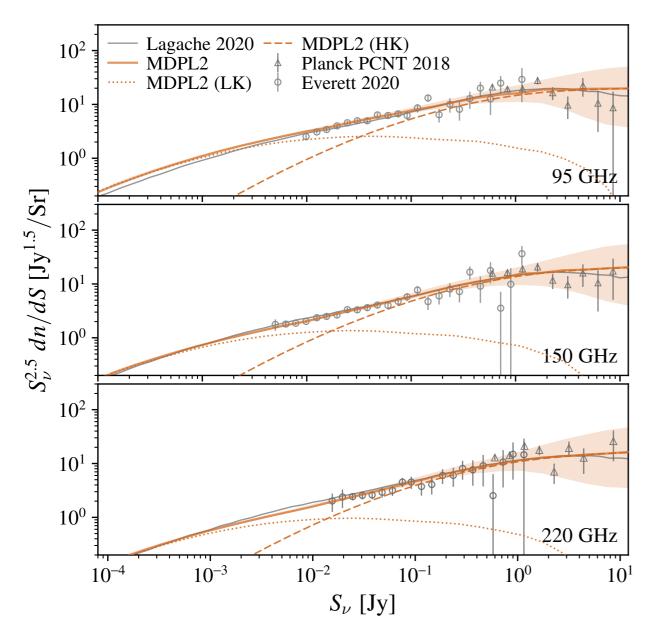
Implementation: Radio

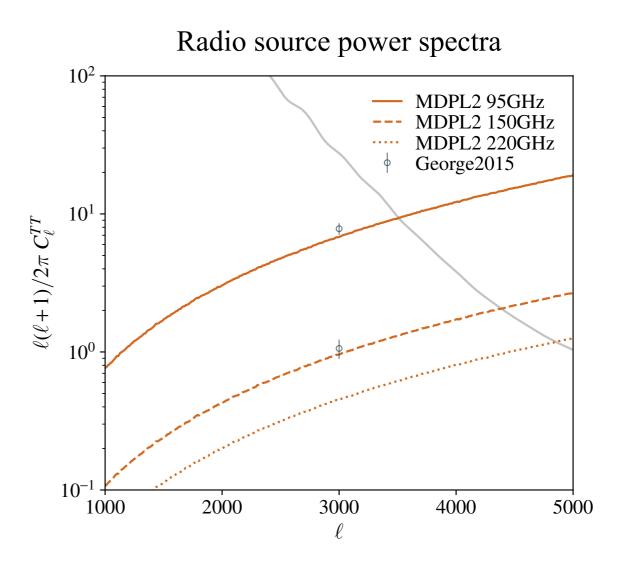
- 1. Start from Rockstar halos.
- 2. Apply UniverseMachine (get M_*/SFR).
- 3. Apply results from TRINITY (to get $M_{\rm BH}$ and fraction of AGNs).
- 4. Do abundance matching with 5GHz luminosity function from <u>Tucci2021</u>.
- 5. Scale the frequency up to match with 150 GHz.
- 6. Scale frequency to 90 and 220 GHz using α_{150}^{90} and α_{150}^{220} derived from data.



Validation: Radio source counts and power spectra

Radio source differential number counts



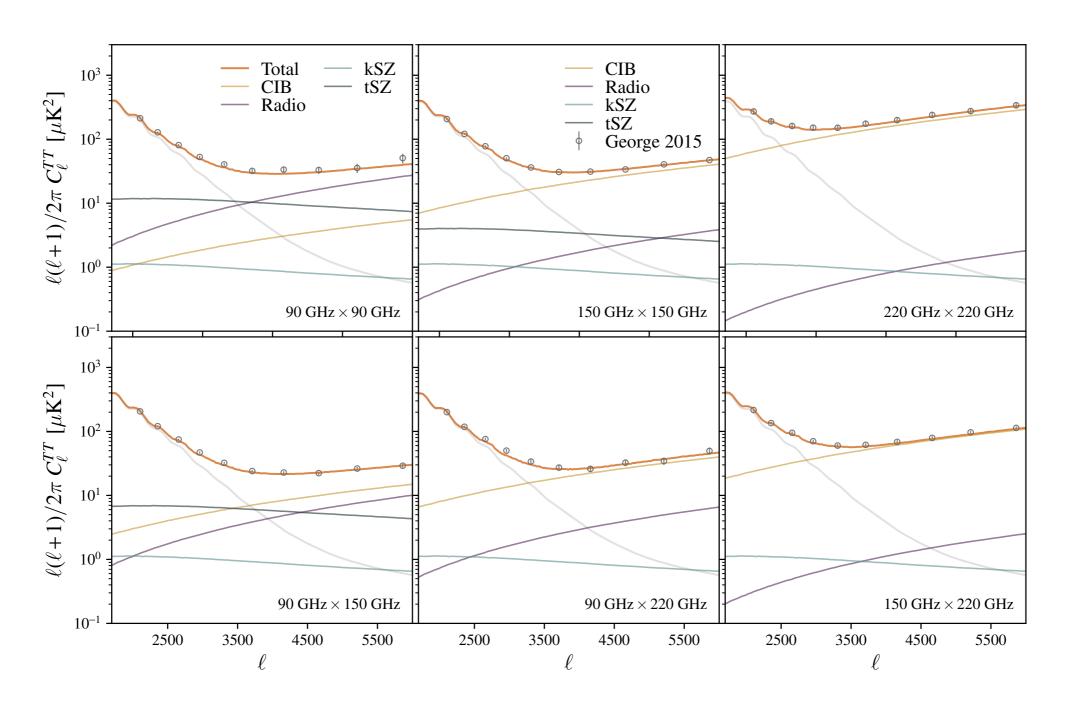


Power spectra

Total 90 GHz map = CMB + kSZ + CIB_{90GHz} + tSZ_{90GHz} + $radio_{90GHz}$

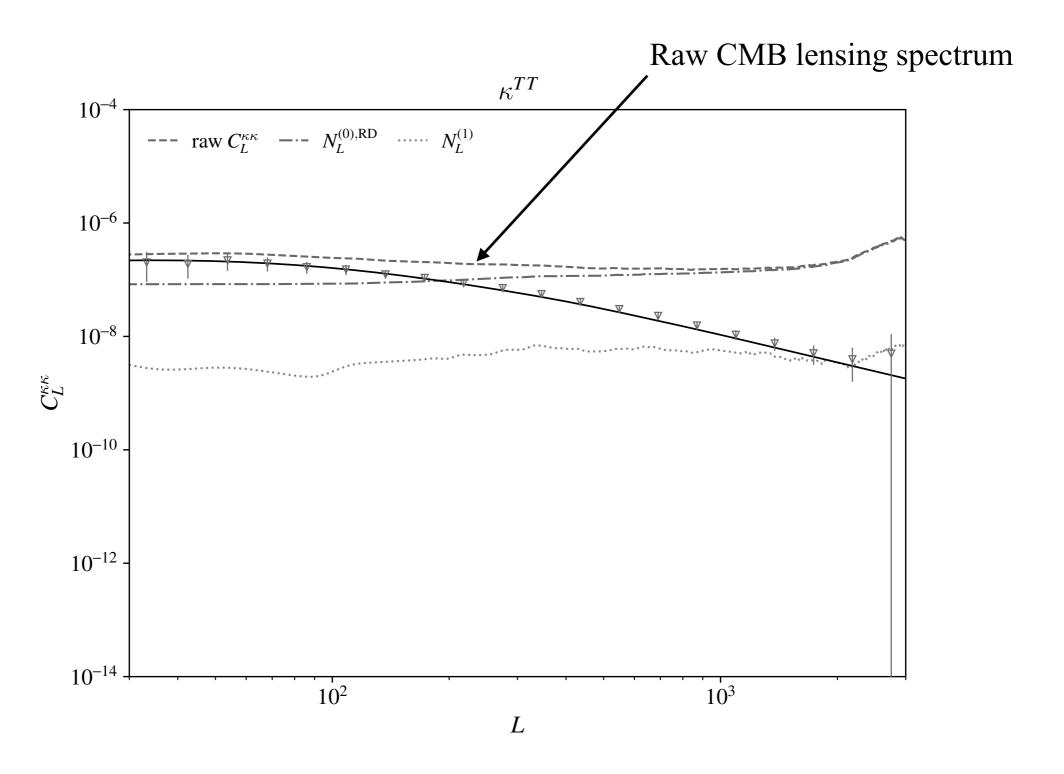
Power spectra

Total 90 GHz map = CMB + kSZ + CIB_{90GHz} + tSZ_{90GHz} + $radio_{90GHz}$

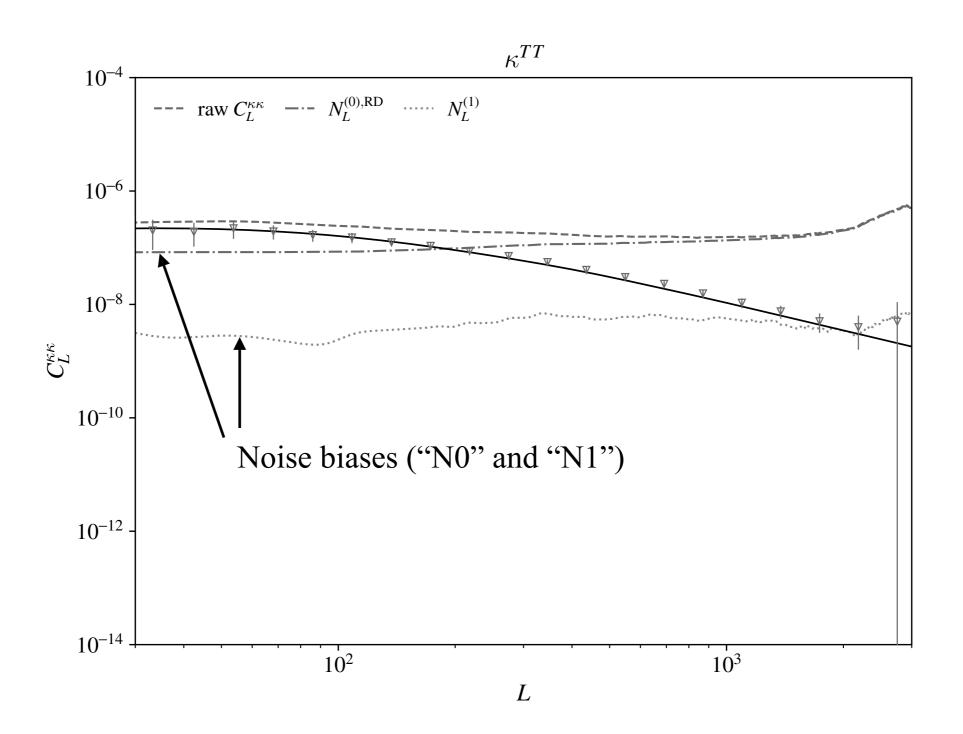


Example usage of MDPL2

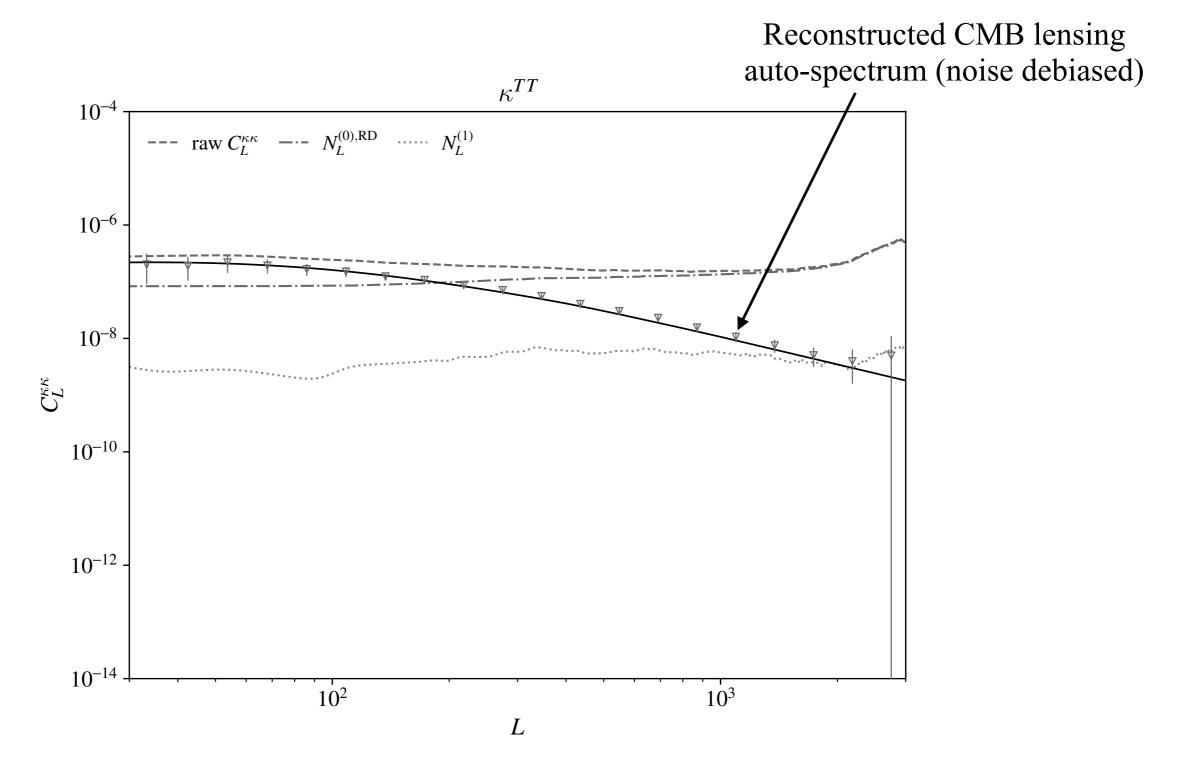
- 1. Biases in reconstructed CMB lensing map
- 2. Biases in reconstructed tSZ maps
- 3. Multi-tracer delensing forecasting



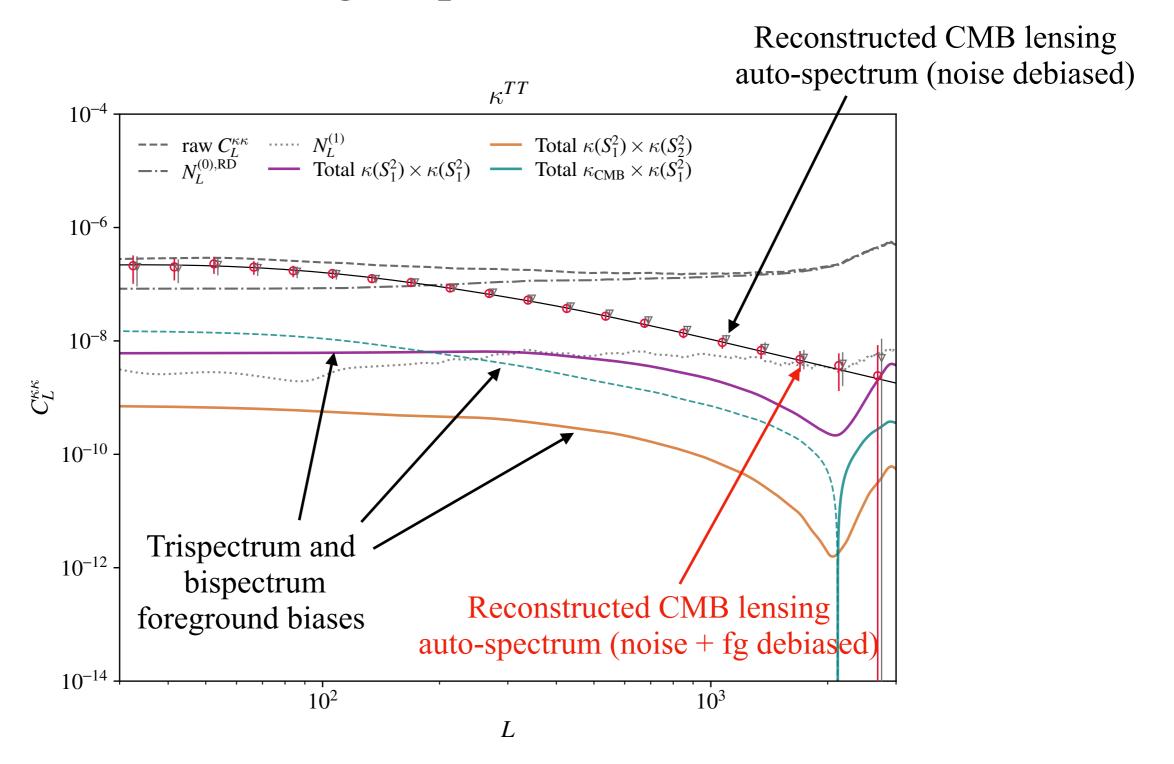
Setup: $5\mu \text{K}$ -arcmin experiment, masking ptsrcs down to 6 mJy, clusters down to $2 \times 10^{14} M_{\odot}$



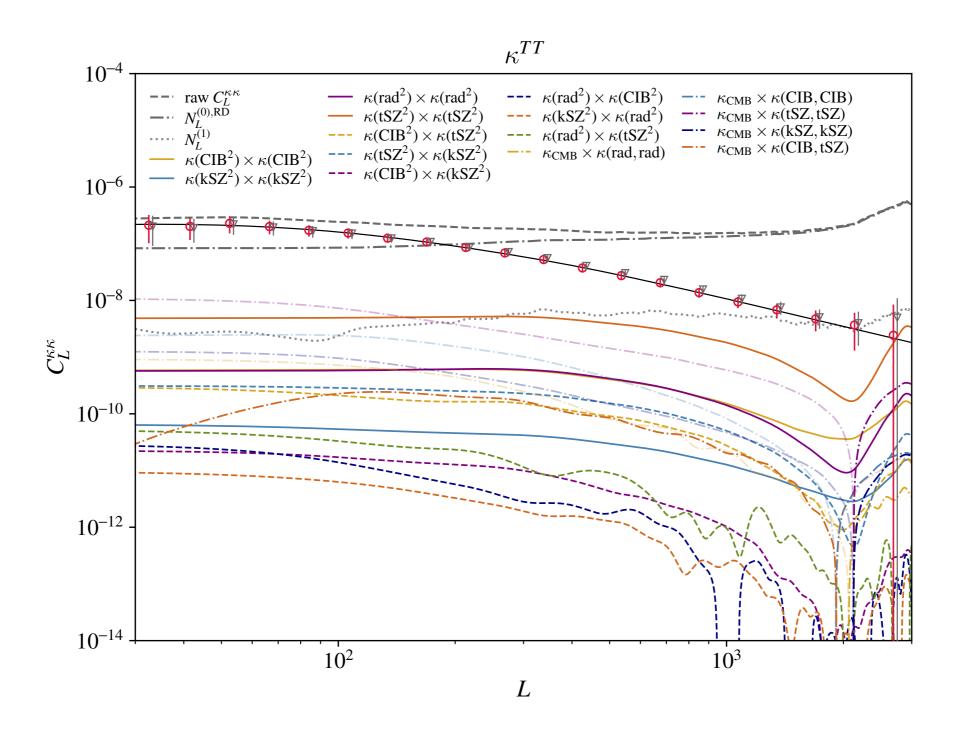
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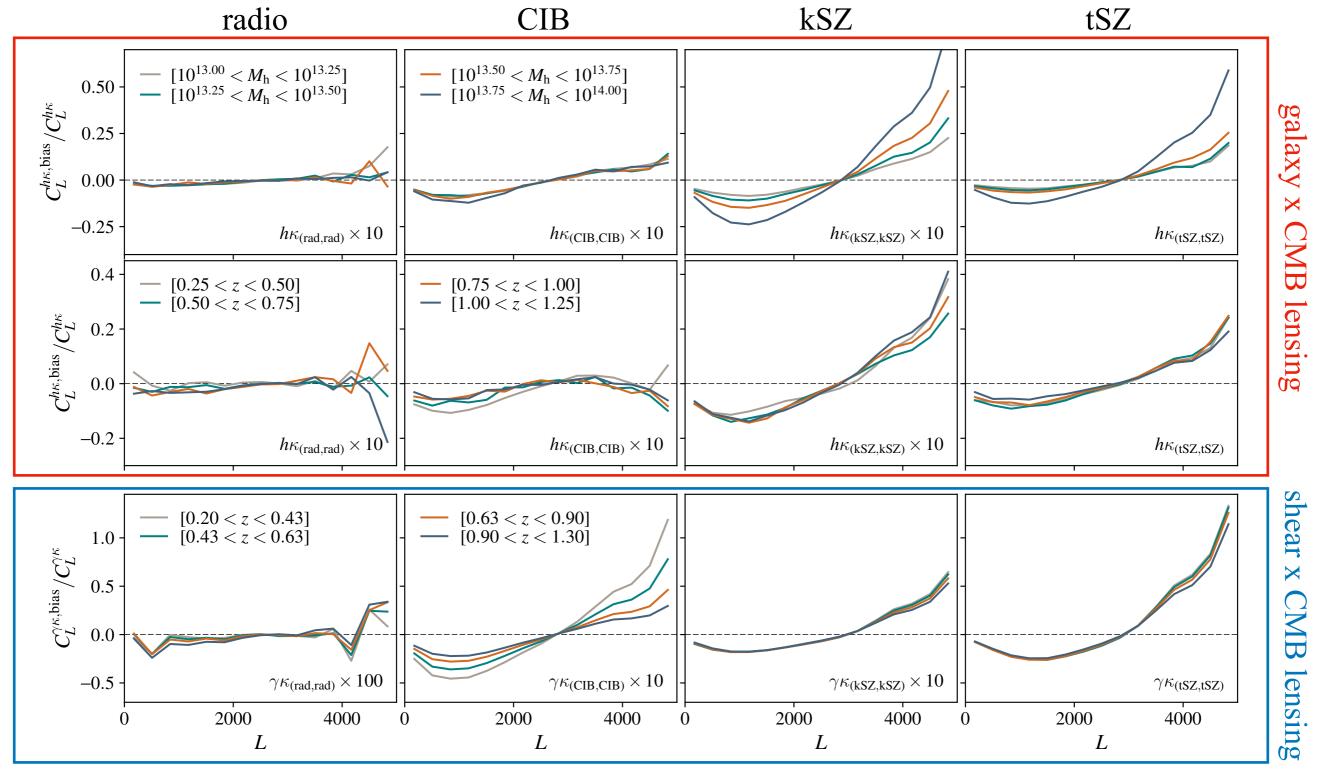
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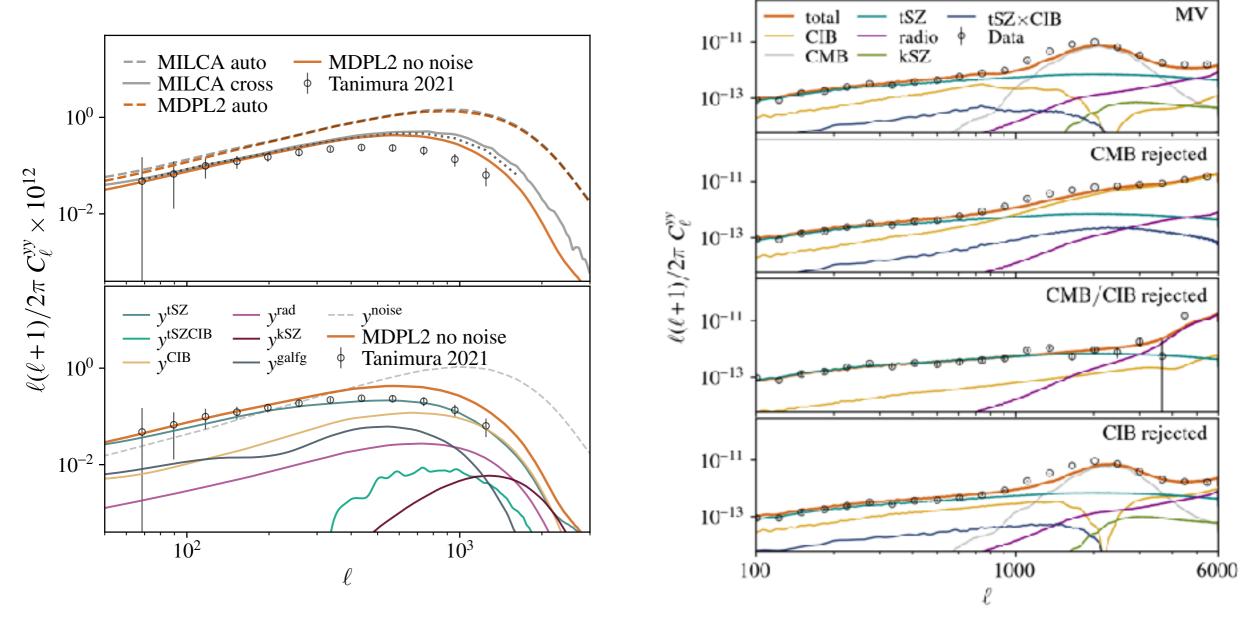
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**Slightly different setup from the previous slide

Biases in tSZ maps

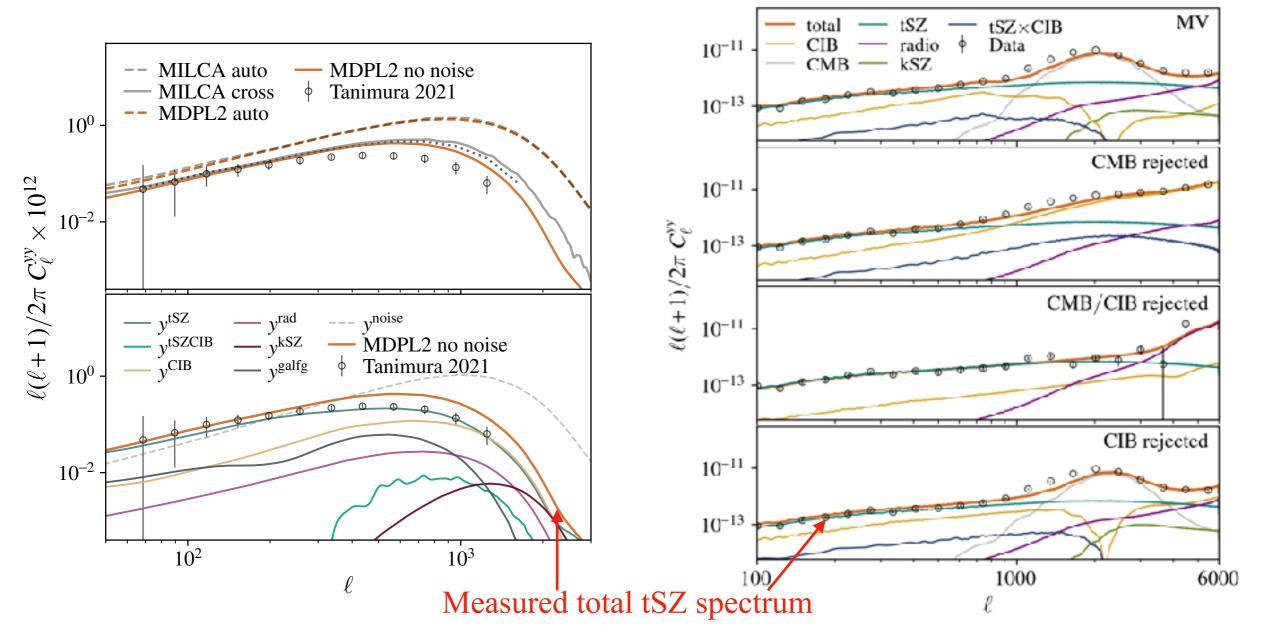
Can also pass frequency maps through *Planck* MILCA/SPT *y*map making pipeline, and investigate biases in those maps.



We can understand which foreground components are responsible for the various "features" in the power spectrum.

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Biases in tSZ maps

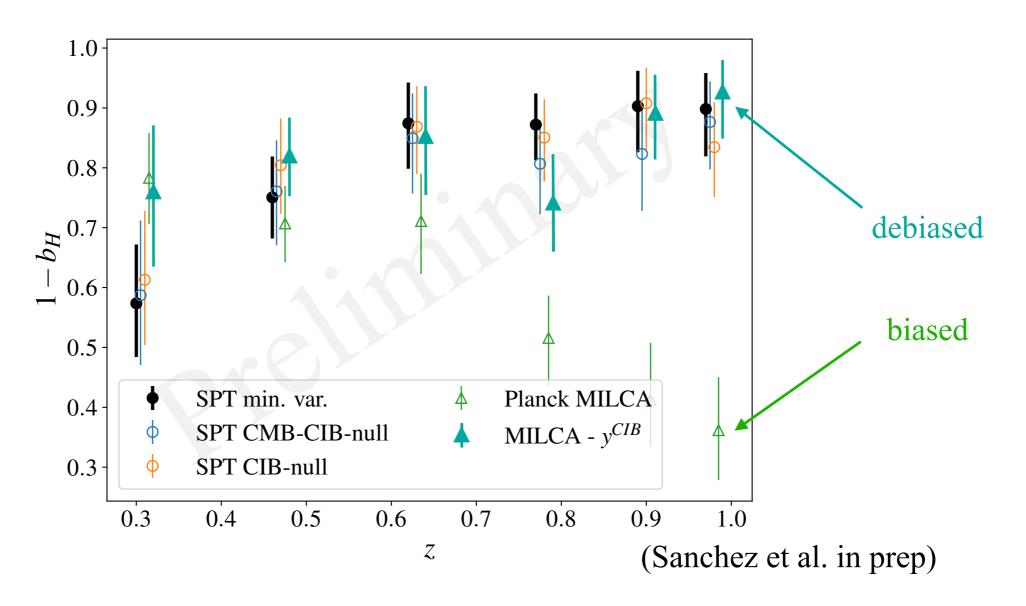
We can identify biases in crosscorrelations and estimate the bias using the combination of data simulations.

Specially for MILCA, we find that there is a lot of CIB contamination in $tSZ \times galaxies$ correlation.

$$P_{e}(r) = P_{*} \times p(r/r_{500c})$$

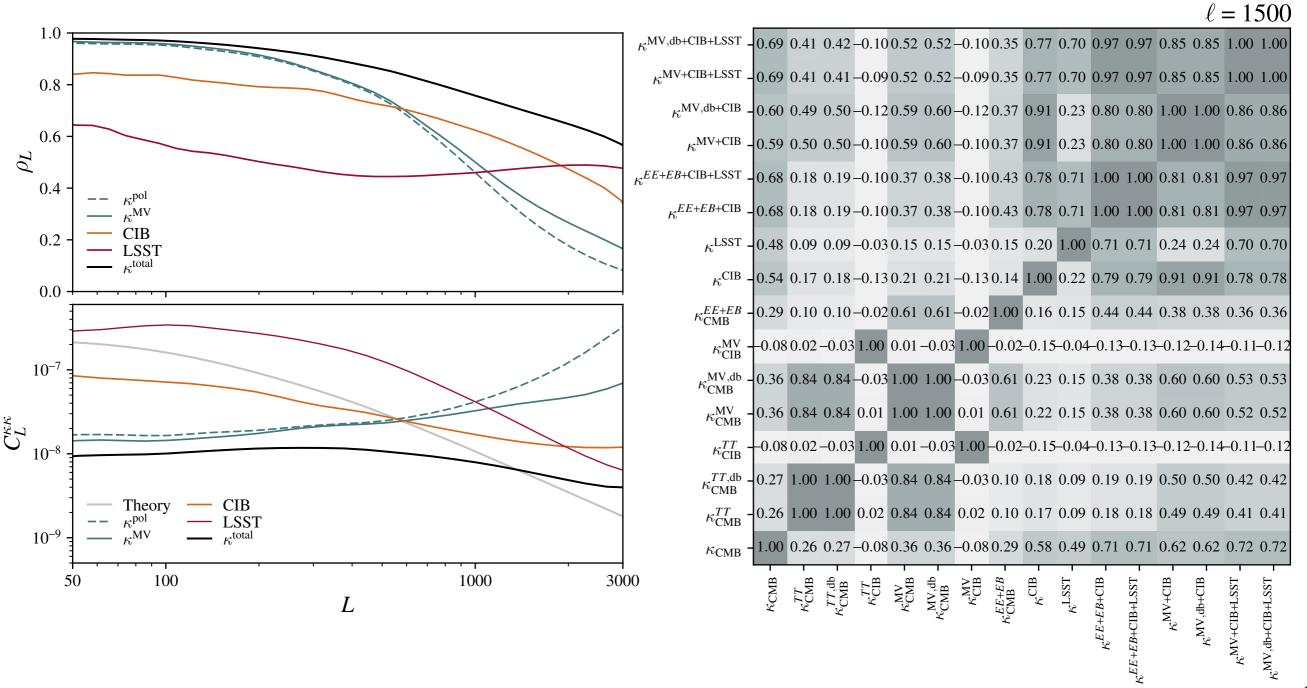
$$p(x) = (c_{P}x)^{-\gamma} \left[1 + (c_{P}x)^{\alpha} \right]^{\frac{\gamma - \beta}{\alpha}}$$

$$P_{*} = P_{0} \left(1.65 \text{ eV cm}^{-3} \right) h_{70}^{8/3} \left(\frac{h_{70}(1 - b_{H}) M_{500c}}{3 \times 10^{14} M_{\odot}} \right)^{0.79}$$



Multi-tracer delensing forecasting

One of the key science for Stage-3 and Stage-4 CMB experiments is to constraint r, and we want maximize the delensing efficiency by throwing every possible data to improve our estimate of the lensing potential. \rightarrow Combine internal lensing + CIB + LSS



Part II summary

- MDPL2 synthetic sky simulation is one of the few simulations that have both CMB and LSS simulation products, tested to the level that is usable for real data analyses.
- The modelling is calibrated against existing observational data and external hydrodynamical simulations.
- It was built with a focus on accurate modelling of the CMB foregrounds, for the purpose of assessing biases in auto/cross-correlation measurements of SZ/lensing.
- MDPL2 is already being used for several analyses e.g. 6x2pt, galaxies × tSZ, shear × tSZ, pairwise kSZ, multi-tracer delensing forecasts etc.
- Future/On-going works:
 - Implementation of more realistic LSST galaxies
 - Baryonification
 - Learning from MDPL2 and pasting secondaries to cheaper mocks
 - LIM
 - Other observables (X-ray, clusters, patchy kSZ etc.)